University of Stavanger

Faculty of Science and Technology

MASTER'S THESIS

Study program/ Specialization: **Societal Safety / Fire safety engineering**	Spring semester, 2014 Open access
Writer: **Hjalte Bengtsson**	……………………………………………………… (Writer's signature)

Faculty supervisor: **Ove Njå**

External supervisor(s): **Grunde Jomaas** (Technical University of Denmark, DTU)

Thesis title:

Development of a Framework for Application of Bayesian Networks in Fire Safety Engineering in Denmark

Credits (ECTS): **30**

Key words: **Risk-based design, building fire safety, Bayesian network, TRANSIT, road tunnel**	Pages: 63 + enclosure: 12 Stavanger, 28-07-2014 Date/year

Master's Thesis

Development of a Framework for Application of Bayesian Networks in Fire Safety Engineering in Denmark

Hjalte BENGTSSON

July 2014

Development of a Framework for Application of Bayesian Networks in Fire Safety Engineering in Denmark

---

Author:
Hjalte Bengtsson
hjalte.bengtsson@outlook.com

UiS student ID: 226967
DTU student ID: s082504

UiS supervisor:

Professor
Ove Njå

University of Stavanger
Faculty of Science and Technology
Department of Industrial Economics, Risk Management and Planning
N-4036 Stavanger
NORWAY

www.uis.no

DTU supervisor:

Associate Professor
Grunde Jomaas

Technical University of Denmark
Department of Civil Engineering
DK-2800 Kgs. Lyngby
DENMARK

www.dtu.dk

Document compilation date: 28th July 2014

This document has been prepared for two-sided printing

Abstract

Studies have found that deterministic performance-based fire safety design leads to unnecessary high safety levels in buildings in Denmark. Other studies have described that prescribed fire safety regulations leads to safety levels that vary based on the type of occupancy and the type of fire safety concept. Additionally, it has been found that designers do not focus on the safety margin of designs, which leads to further inconsistency in the safety levels of different buildings. These issues are problematic for building developers and building users as resources are wasted on fire safety installations and systems that are not necessarily required.

A risk-based design approach has been suggested as a solution to the problems. However, risk-based methods require reliable models and data to adequately describe the safety level of a building. The first goal of the present study was to assess the potential of using Bayesian networks to improve current fire risk analysis methods.

The study found that Bayesian networks have significant advantages compared to the tools currently used in fire safety engineering in Denmark — for example fault and event trees. The advantages include the enhanced ability to model interconnected phenomena and the possibility to model variables more detailed than a mere binary representation. Based on these qualities, the study found that the use of Bayesian networks could improve fire risk analyses.

However, it was also found that a methodology for successful application of Bayesian networks in fire safety engineering has not been developed. Therefore, the second goal of this study was to develop a framework for the application of Bayesian network models in fire safety engineering.

The framework was developed based on different Bayesian network models for use in fire risk analysis found in the literature. However, these models were not deemed adequate to describe all the challenges regarding implementation of a new tool in practice. Therefore, it was investigated how a state of the art Bayesian network model called TRANSIT has been applied in assessment of road tunnel safety.

TRANSIT was found to be a holistic model with focus on both incident occurrence and consequences. The model was evaluated based on a complex road tunnel called Rogfast in order to test the limitations of TRANSIT. The evaluation showed that there was some fundamental flaws in the model, for example in the way the model handles uncertainty. Despite this, several concepts used in TRANSIT were found to be applicable for fire safety engineering purposes. These concepts included how to spilt a building in segments with a uniform risk level and how to combine different parameters in a central factor in order to easier model for example occurrence of unwanted events.

Based on the evaluation of TRANSIT and the Bayesian network models found in the literature, 19 recommendations to the use of Bayesian networks in fire safety engineering was formulated. These recommendations form the basis of the framework. The recommendations was separated in four main categories: (i) Categorisation and limitation of models, (ii) key variables to include, (iii) modelling methods and (iv) methods for handling uncertainty. The full list of recommendations is seen in table 5.2 on page 56.

In closing, it was found that explicit acceptance criteria are needed in order to maximise the potential of risk-based methods in fire safety engineering. In Denmark, there is currently no such criteria, thus, for the time being Bayesian network models can only be used to compare the risk level in different buildings or to model failure of sub-systems or processes.

Keywords: Risk-based design, building fire safety, Bayesian network, TRANSIT, road tunnel

Preface

This master's thesis is made in fulfilment of the requirements for the author to obtain his master's degree (M.Sc.) in civil engineering at the Technical University of Denmark (DTU). The work has been conducted at the University of Stavanger (UiS) and the primary supervisor has been professor Ove Njå. The workload of the project corresponds to 30 ECTS points.

Associate professor Grunde Jomaas has been the supervisor from DTU and has provided guidance with respect to the Danish perspectives as well as more general inputs to the work.

Motivation

The motivation for this work came during the final semesters of my study. During classes of building fire safety and risk management, a question arose: How come the state of the art methods of general risk assessment are not better utilised in building fire safety engineering? Although the Danish regulations allow risk assessment to be used in the design and approval phases of new buildings, it seemed that the engineers in the construction industry did not fully benefit from the potential in the regulations. From my perspective, it looked as though building designs and safety levels could be both more efficient, consistent and innovative if improvements were made to current practices. More streamlined methods could also lead to fire safety engineering being better integrated in the design process instead of being a cumbersome add-on engineering discipline, I thought. Therefore, it seemed logical to spend the time working on my master's thesis to study the potential of implementing a new method in Danish and possible international fire safety engineering practices.

The thesis is written for fellow master's students, researchers and fire safety professionals with a passion for the risk perspective in fire safety engineering. It is my hope that the concepts and ideas presented will be an inspiration for future work and that the study will give rise to a discussion and reflection on how we can better utilise the resources in our society based on improved risk-informed decision making.

Acknowledgements

This work has yielded more than just professional knowledge; it has widened my perspective on myself and the world in general. This is especially due to my stay at the University of Stavanger and all the nice people I have met there. Therefore, I would like to thank all the people that have helped making my stay a great experience — especially the Kleiven family. Also, I would like to send a very special thanks to my neighbours and friends at the Sola Sjö dormitory without whom the long working hours and at times dismal weather of south-western Norway would have been hard to get through in a good mood.

My supervisors, professor Ove Njå and associate professor Grunde Jomaas, deserve a sincere thank, too — both for setting up the arrangements for my stay in Norway and for their professional help and competent inputs to the work; all of which is greatly appreciated. Also, I am very grateful for the information on TRANSIT and Rogfast provided by Dr. Henrik Bjelland.

This thesis concludes almost 20 years of schooling from primary school through high school to university. Therefore, I would like to thank all the great, inspiring and passionate teachers I have had the pleasure of being taught by during this time.

Finally, I would like to send my warmest thanks to Ida, Anne, Poul, Toke and Pil — your love and great support means everything to me.

Hjalte Bengtsson
Stavanger, July 2014

Contents

Abstract iii

Preface v

Contents vii

1 Introduction 1
- 1.1 Goal and Methodology . . . 2
  - 1.1.1 Work Concept . . . 3
  - 1.1.2 Case Selection . . . 3
- 1.2 Introduction to Building Fire Safety . . . 4
  - 1.2.1 Fire Risk Assessments . . . 6
- 1.3 Definition of Risk . . . 7
  - 1.3.1 Frequentist Perspective on Risk . . . 7
  - 1.3.2 Bayesian Perspective on Risk . . . 8
- 1.4 Thesis Overview . . . 9

2 Bayesian Networks in Fire Safety Engineering 11
- 2.1 Why Use Bayesian Networks? . . . 11
- 2.2 Existing Models . . . 12
  - 2.2.1 Fire Spread . . . 12
  - 2.2.2 Risk to Occupants . . . 13
  - 2.2.3 Holistic Fire Risk Models . . . 13
- 2.3 Preliminary Conclusions . . . 14

3 TRANSIT and the Rogfast Tunnel 17
- 3.1 Introduction to Road Tunnel Safety . . . 17
- 3.2 The TRANSIT Model . . . 18
  - 3.2.1 Aim and Applications . . . 19
  - 3.2.2 Architecture of TRANSIT . . . 20
  - 3.2.3 Key Assumptions . . . 22
  - 3.2.4 Analysis of the AMF Node . . . 23
- 3.3 The Rogfast Project . . . 25

3.3.1 Description of the Tunnel . . . 27
3.3.2 Risk Assessments . . . 28
3.3.3 Challenges . . . 31
3.4 Preliminary Conclusions . . . 32

4 Evaluation of TRANSIT 33
4.1 TRANSIT in General . . . 33
4.1.1 Performance Goals . . . 33
4.1.2 Rigour versus Relevance . . . 34
4.1.3 Uncertainty in TRANSIT . . . 36
4.1.4 Output . . . 37
4.2 TRANSIT in Rogfast . . . 38
4.2.1 Insufficiencies of TRANSIT . . . 38
4.3 Preliminary Conclusions . . . 40

5 Framework for Application of Bayesian Networks 41
5.1 Categorisation and Limitation . . . 42
5.1.1 Categorisation of Buildings . . . 42
5.1.2 Level of Detail . . . 43
5.1.3 Context . . . 44
5.1.4 Applicability . . . 44
5.2 Key Variables . . . 45
5.2.1 The Fire . . . 45
5.2.2 Systems and Environment . . . 46
5.2.3 Occupants . . . 46
5.2.4 Emergency Service . . . 47
5.3 Modelling Method . . . 48
5.3.1 Data Collection . . . 48
5.3.2 Segmentation . . . 49
5.3.3 Centralisation of Variables . . . 49
5.3.4 Degree of Flexibility . . . 50
5.4 Handling of Uncertainties . . . 51
5.4.1 Communication . . . 52
5.4.2 User Access to Assumptions . . . 52
5.4.3 Uncertainty of Input . . . 52
5.4.4 Sensitivity of Variables . . . 53
5.4.5 Model Uncertainty . . . 54
5.5 Summarising the Framework . . . 54

6 Discussion 57
6.1 Assessment of Methods . . . 57
6.1.1 Case Study Approach . . . 57
6.1.2 Risk Perspective . . . 58
6.2 Risk-Based Design in a Danish Perspective . . . 58

7 Conclusion 61
7.1 Further Research . . . 62

Bibliography **65**

APPENDICES **73**

A Theory on Bayesian Networks **73**
A.1 History and Applications 73
A.2 Definitions 74
A.3 States and Evidence 76
A.4 Connections and Separation 76
A.5 Continuous Variables 77

B Road Tunnel Safety **79**
B.1 Traffic Accidents in Road Tunnels 79
B.2 Fire in Road Tunnels 81
B.2.1 Historic Road Tunnel Fires 81
B.3 Accidents involving Hazardous Materials 81

C TRANSIT Networks **83**

Chapter 1

Introduction

Building fires have been a threat to occupants and property for as long as buildings have existed. Therefore, building codes around the world have incorporated demands that must be fulfilled in order to ensure that buildings have a reasonably level of protection against fire. Previously, prescriptive design codes have been used to ensure building designers applied similar fire safety concepts in all buildings. However, during the last decades many countries have introduced performance-based design codes for different reasons. These reasons include a wish for deregulation, trade facilitation and to allow more innovative building designs (Meacham et al., 2005). In Denmark, performance-based designs have been accepted since 2004, when amendment 8 to the building regulations at the time became effective (DBHA, 2004b).

Currently, building designs in Denmark can be based on two different documents: The pre-accepted solutions Danish Energy Agency (2012) and the guideline for performance-based design DBHA (2004a). The latter document describes both deterministic and risk-based approaches to performance-based design with the deterministic approach being the far most adopted of the two.

However, in the Danish building industry, there is a concern that the deterministic performance-based fire safety approach may underestimate the safety level of buildings compared to the classic prescriptive designs, thus leading to unnecessary high levels of safety (Hede, 2011). This is a problem as building costs increase as excess fire safety measures are installed. Hede (2011) investigated the problem by conducting both a deterministic and a risk-based analysis of an office building designed using the Danish prescriptive fire safety regulations. She found that the performance-based analysis rejected the design, whereas the risk-based analysis approved it. Thus, Hede (2011) concluded that the claim in the industry is justified.

However, the solution is not to return to strictly prescriptive design codes as studies have shown that the safety levels of both different types of occupancies (Yilmaz, 2013) and different types of prescriptive fire safety concepts (Bjelland and Njå, 2011) vary considerably. In other words, prescriptive designs do not yield the desired consistent safety levels throughout the built environment either.

Instead, a solution to the problem could be to adopt risk-based approach — see e.g. Meacham (2010). This approach take case-specific factors into account like the deterministic performance-based approach, but additionally, the risk-based approach add the dimension of probability of occurrence. As a result, the full risk picture is better described and, therefore, the risk-based approach potentially leads to more consistent and uniform safety levels despite differences in building design and usage.

However, designers need both credible tools and data in order for valid engineering decision-making to be consistently conducted with a risk-based approach. In Denmark, the current risk assessment tools and methods described in the Danish performance-based fire safety guideline (DBHA, 2004a) are relatively unsophisticated compared to for example the methods used in the oil and gas industry and other businesses — see e.g. Rausand (2011). Moreover, most models concerned with fire safety and fire risk considers only one or few aspects such as smoke and fire spread or safe evacuation of occupants. Few models consider the interactions between the different parameters needed to assess the overall risk level of a building (Hanea and Ale, 2009).

Therefore, this work will study and evaluate how Bayesian networks can be used in fire safety engineering as this tool is thought to be well-suited for complex systems with a high number of interactions between sub-systems (Rausand, 2011). In short, the study will investigate how Bayesian networks previously has been used in fire risk analyses, and a state of the art Bayesian network model called TRANSIT — which is used to assess road tunnel safety — will be analysed and assessed in order to learn from other fields of engineering science.

The goals of the study are (i) to assess the potential of using Bayesian networks in fire safety engineering, and (ii) to develop a framework for how to apply Bayesian network models for assessing fire risk. The framework will consist of a list of recommendations to future Bayesian network models. These recommendations will describe how to best utilise the tool and how to best address fire risk in such models.

In order to achieve the goals, this first chapter will continue by describing the methods used in the study and the reasoning behind the choice of TRANSIT as a case. Then, a short overview of general fire safety engineering methods and concepts is given in order to understand the basis of the work. Afterwards, section 1.3 gives a brief introduction to risk in order to establish a platform for the following analyses. Finally, an overview of the rest of the thesis is given, leading to the presentation of the actual work of the study in the subsequent chapters.

1.1 Goal and Methodology

As mentioned, one of the goals of the study is to assess the potential for using Bayesian networks as a tool in fire risk analysis. This goal must be achieved before the second goal — how Bayesian networks can be used — can be accomplished.

Both goals will be partly achieved by a literature survey. However, as seen later in this work, the models in the literature are rather academic and not refined enough to be directly applied in practice. Therefore, an analysis of the concepts, the structure, and the application of the road tunnel risk assessment model TRANSIT will be used in order to gain insight into how such models can be used in practice. TRANSIT will be analysed both by investigating the model in a general perspective and by evaluating the use of it in a Norwegian road tunnel project called Rogfast. Thereby, this study will adopt both a literature study and a case study approach.

Case studies are described as a research strategy, where a study of a certain phenomenon is conducted in the context, and where the boundaries between the context and the phenomenon are not clearly defined (Yin, 1981). Here, the phenomenon is the use of TRANSIT in risk assessment of Rogfast and the context is risk assessment using Bayesian networks in the construction industry.

According to Eisenhardt (1989), the strength in using case studies lies in the possibilities to investigate how theory works in practice. She also states that the outcome of a case study is empirically valid and as such allows researchers to review current theory, knowledge and methods. Additionally, Eisenhardt (1989) describes the iterative processes of building theories from case study research. Eisenhardt's processes include selection of case and how to compare findings and literature. She points out that it is essential to compare own conclusions with critical and contradicting literature as this allows both to better understand the opponent and to formulate counterarguments, which helps better understand own findings. The current study has been made with this in mind.

1.1.1 Work Concept

Figure 1.1 shows the concepts of the work process in this study. The rectangular nodes represent the studies and analyses conducted in relation to this work, whereas the ellipsoid nodes represent input from other sources. Thereby, this work consists of three main parts — a literature survey of existing methods and models (chapter 2), an analysis of the use of Bayesian networks in risk assessment of road tunnels (chapters 3 and 4) and development of a framework for use of Bayesian networks in fire safety engineering (chapter 5). As described, the basic idea is both to learn from existing fire-related Bayesian networks and to learn from the broader field of risk analysis in order to improve current practices in the Danish fire safety industry; this crossover is represented by the horizontal dashed line in figure 1.1. The dashed arrow between the potential for improvement and the framework represents feedback, which is a part of the iterative process described by Eisenhardt (1989).

1.1.2 Case Selection

An application of Bayesian networks in road tunnel safety is interesting in relation to the field of building fire safety for at least two main reasons: (i) Evacuation of persons is key in both tunnels and buildings, and because (ii) fire safety is a key concern in both tunnels and buildings. The use of TRANSIT is interesting as the model is state of the art, and because it is designed to be the base of future work in risk assessment of road tunnels (Schubert et al., 2012b).

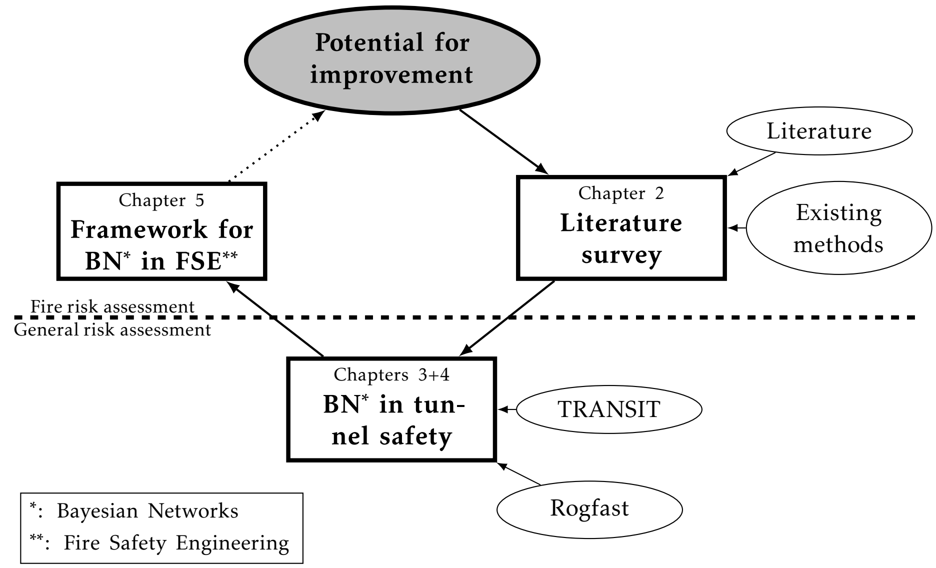


Figure 1.1: Conceptual work flow of this work. The horizontal dashed line symbolises the boundary between the field of general risk assessment (below) and the field of fire risk assessment (above). The dashed arrow symbolises the feedback given in an iterative process.

Eisenhardt (1989) suggests that cases representing extremes should be chosen as they are more likely to extend the current knowledge in the given field of research. Following this reasoning, the case selected for evaluating TRANSIT in practice should represent an extreme. Some of the longest road tunnels in the world are found in Norway, and Norway is the country with most sub-sea road tunnels in the world (Nævestad and Meyer, 2014). The Rogfast tunnel has been selected as a case for this study as it is to be the world's longest and deepest sub-sea road tunnel (NPRA, 2014). Thus, Rogfast may be defined as an extreme representative for further research.

1.2 Introduction to Building Fire Safety

With the motivation and study goal presented, the next step in this work is to establish a basic knowledge on fire safety engineering, which is needed in order to understand how to apply the principles from Bayesian network theory in practice. Therefore, this section describes the foundations of fire safety science and fire risk assessment methods.

In short, the field of building fire safety deals with both preventing fires from happening and designing systems that mitigate the effects of a fire. Generally, this is done by designing and dimensioning both emergency exits, building structures and smoke management systems as well as developing methods for handling fire hazards. This implies knowledge of physics in order to understand the dynamics of a fire, material behaviour, human behaviour etc. (Spearpoint, 2008). The challenge is to meet the wishes of the architects and building developers to design modern and open buildings without compromising safety.

According to the New Zealand Centre for Advanced Engineering (CAENZ) (Spearpoint, 2008), the parameters seen in table 1.1 influence the fire safety level of a building and can be used as a rough list of factors to assess in a building fire risk analysis. The parameters in the table corresponds to the ones described in the Danish fire safety design guidelines (DBHA, 2004a; Danish Energy Agency, 2012).

More specifically, there are two strategies to achieve fire safety: (i) prevent fire ignition or (ii) manage the impact of a fire. The fire safety concept tree from NFPA 550 (2012) describes the different factors that influence the two strategies. Prevention of fire ignition can be done by controlling heat sources, controlling the available fuel or controlling the possible heat source/fuel interaction. The fire impact can be managed by controlling the fire or controlling the exposed.

In deterministic performance-based designs, occupant safety is often evaluated using the Evacuation Safety Level (ESL) given in terms of the Available Safe Egress Time (ASET) and the Required Safe Egress Time (RSET) as seen in equation (1.1) (Nelson and Mowrer, 2002).

$$\mathrm{ESL} = \frac{\mathrm{ASET}}{\mathrm{RSET}} \tag{1.1}$$

Calculations of the ASET and RSET may include specialised CFD models to model smoke and fire spread and evacuation models to calculate the time for the occupants to evacuate. Additionally, fire tests can be used to assess and classify the fire safety properties of materials and construction products (Spearpoint, 2008).

However, the ASET/RSET method has been a subject of criticism despite it being widely used and is the predominant method in Danish performance-based designs. Babrauskas et al. (2010) claim that excessive focus on the ESL may lead fire safety engineers to ignore the large variations in fire scenarios and occupant behaviour. Additionally, Bjelland and Njå (2012) found that the ASET/RSET method is often used to verify the chosen design instead of developing it. Thereby, designers do not investigate the safety margin of the design. Thus, these problems

Table 1.1: Factors that influence the fire safety level of a building according to CAENZ (Spearpoint, 2008).

• Building geometry and intended use	• Number, location and abilities of occupants
• Location of adjacent properties	• Proximity and likely response of the fire services
• Probability of a fire occurring	• Building management practices
• Fuel load and distribution	• Fire safety installations

could be some of the causes for the underestimation of the fire safety level in deterministic performance-based designs discussed above.

1.2.1 Fire Risk Assessments

As argued, a risk-based approach to design could solve some of the problems with deterministic performance-based designs. Risk-based designs are based on fire risk assessments with the following purposes: (i) Identification of fire hazards, (ii) estimation of the consequences and the probability of fire hazards, (iii) identification of design options that mitigate the unwanted risks, (iv) determination of appropriate fire protection measures and (v) communication of the findings to different stakeholders such as the building owners, authorities and insurance companies (Watts and Hall, 2002). Often, separate analyses of probabilities and consequences are conducted as seen in figure 1.2, which shows the principal four-step process for estimating fire risk presented by Hall and Watts (2008).

Fire risk assessments can be either qualitative or quantitative (Yung, 2008). According to British Standard (BS 9999, 2008), they should include analysis and assessment of (i) likelihood of fire occurrence, (ii) anticipated fire severity and potential fire spread, (iii) structural fire resistance, (iv) consequential danger to persons in and around the building and (v) the need to address fire impact on property, environment etc. (as a supplement to the assessment of occupant safety).

The Danish guideline for performance-based design (DBHA, 2004a) states that fire risk assessments can be required for buildings that are complex or untraditional, however, only the events after initiation of a fire is considered in such an analysis and, typically, the scenarios considered are limited to worst cases. Thereby, the part of the fire safety concept tree dealing with the probability of fire occurrence is not considered. Additionally, the focus on worst case scenarios means that the cases, where a fire occurs without causing much damage, are left out of account. The reason for this could be lack of both data, knowledge and valid models that covers the entire fire safety concept tree.

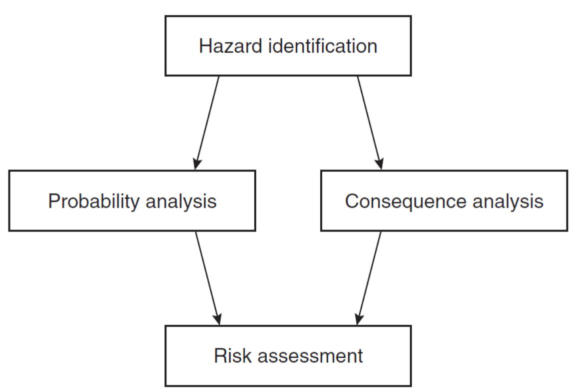


Figure 1.2: The principal process of estimating fire risk (Hall and Watts, 2008).

Bayesian network models could be used to better model interactions of fire safety systems by covering more aspects of the processes, thereby improving the value of fire risk assessments in design decision-making. This perspective is further described and discussed in chapter 2.

1.3 Definition of Risk

The final concept that has to be discussed before continuing to the matter of this study is the definition of risk. The term *risk* is used in different contexts, but the exact meaning is not always clear. This section will briefly describe different perspectives on risk in order to understand the foundation of risk analyses, whether it be a risk analysis of a road tunnel or a fire risk analysis of a building.

The international standard on risk management (ISO 31000, 2009) defines risk as the effect of uncertainty on objectives. Often, risk is conceived as the answer to the following three questions (Rausand, 2011):

- What can go wrong?
- What is the likelihood of that happening?
- What are the consequences?

However, there are several interpretations of how to describe risk. The two most prevailing conceptions are the *Frequentist* or classical perspective and the *Bayesian* perspective. It is important to understand the limitations and differences of the two in order to follow some of the conclusions drawn later in this work. Therefore, the next two sections will briefly outline the fundamental philosophies of the two conceptions.

1.3.1 Frequentist Perspective on Risk

Basically, Frequentists see probability as an objective and true value that can be studied for example by looking at statistical data. Thus, Frequentists believe that probability expresses the fraction of times a particular outcome will be observed if an infinite number of repetitions were made. In this perspective, uncertainty is the difference between the true probability and the one used by the analyst. Frequentists often present risk as for example the expected number of accidents or fatalities per year, hence the name "Frequentists" or the relative frequency-based approach (Aven and Heide, 2009).

Frequentists calculate risk as the probability of an event times the consequence of the event, hence an expected value of probabilities and consequences form the risk conception. Several events may be hazardous and in such cases the total risk is the sum of all the risks. This is described by equation (1.2), where P_i and C_i are the probability and consequence, respectively, of event i and n is the total number of hazardous events — see e.g. (Ale, 2009; Faber, 2012).

$$R = \sum_{i=1}^{n} P_i C_i \tag{1.2}$$

The Frequentist perspective is criticised, because it can be difficult to make decisions based on this definition of risk as nothing is said about the variation of the different outcomes when a single number is describing the risk level. Thus, low-probability/high-consequence events may be overlooked by decision makers as equation (1.2) produces an average value. Aven (2010) argues that decision-makers might want more information on events that rarely occur, which is not included in this definition of risk.

Aven and Heide (2009) state that the reliability of risk analyses based on this perspective is dependent on the amount of data, and that the validity of the methods is questionable in cases of little data.

1.3.2 Bayesian Perspective on Risk

On the other hand, Bayesians believe probability is a measure of uncertainty about future events and their consequences. As different assessors will have different degrees of uncertainty about a phenomenon, probability in a Bayesian perspective is inherently subjective. Or in other words, Bayesians think probability expresses the subjective belief of the analyst (Aven and Heide, 2009). The belief may be altered when new information becomes available, and this is the fundamental idea behind Bayesian networks (Jensen and Nielsen, 2007) — see also chapter 2 and appendix A.

From this perspective, Aven (2010) suggests that risk should be seen as a two-dimensioned concept including the uncertainty, U, of events, A, and consequences, C. This view takes into account uncertainties such as "*will A occur as predicted?*" and "*will C be the value that was expected?*". Aven (2010) defines this as the (A,C,U) perspective.

The strength of this approach is that it expresses uncertainties, thus it provides decision makers with a wider perspective of possible outcomes of different options. However, this subjective definition of probability opens this approach up for criticism for its inability to produce replicable results — a criterion that is fundamental in most scientific theoretical contexts (Aven and Heide, 2009).

Aven (2010) describes risk from the (A,C,U) perspective by the parameters A, C, U, P, K and S. Here, A, C and U still refer to the events, consequences and uncertainties, respectively, whereas P refers to the probabilities of A and C, and K is the knowledge of U and P. Finally, the sensitivities, S, are included in order to describe how varying inputs affect the result of the risk analysis. With those parameters, Aven (2010) claims to describe the risk picture and the inherent uncertainties in the best possible way.

In this work, risk is described from a Bayesian perspective using Aven's (A,C,U) perspective. This applies both to the evaluation of Bayesian network models such as TRANSIT and to the development of the framework with recommendations to future use of Bayesian networks in fire safety engineering. The Bayesian perspective is adopted as it is thought to be most fitting for describing risk in complex and state of the art systems with little prior knowledge and lack of historical data. This is done despite that the Danish performance-based design guideline has a Frequentist perspective on risk (DBHA, 2004a).

1.4 Thesis Overview

With the basic knowledge and concepts established, the analysis of use of Bayesian networks in fire safety engineering can commence. First, chapter 2 discusses the potential in Bayesian networks and how they have been used in fire safety engineering previously.

Then, chapter 3 describes the TRANSIT model and the Rogfast tunnel project in order to establish the basis of the evaluation of TRANSIT in chapter 4.

Afterwards, chapter 5 develops the framework for application of Bayesian networks in fire safety engineering based on the learnings from the TRANSIT model as well as fire safety related Bayesian network models found in the literature. The framework is presented as a list with 19 specific recommendations separated in four main categories, which is claimed to cover the considerations necessary for a meaningful and fruitful use of the tool.

Finally, the different aspects and perspectives in the work are discussed in chapter 6, before the findings and conclusions are summarised in chapter 7 together with suggestions for further studies in the field.

Supplementary, appendices A and B describe fundamental theory of Bayesian networks and road tunnel safety, respectively, and are intended for readers without basic knowledge of these subjects. Appendix C shows the Bayesian networks used in the TRANSIT model.

Chapter 2

Bayesian Networks in Fire Safety Engineering

This chapter starts out by discussing what Bayesian networks can bring to fire safety engineering. Afterwards, a literature survey of Bayesian networks applied in fire safety engineering is presented. The models described in this part will be used as inspiration for the framework developed later in this work.

Readers that are not familiar with Bayesian networks are encouraged to read appendix A, where the mathematical background and the basic structures of a network are outlined. Additionally, their history and other applications are presented.

2.1 Why Use Bayesian Networks?

As mentioned, credible and sound tools are needed if a risk-based approach is to be adopted in fire safety engineering. The tools currently used in the field include fault and event trees among several other methods — see e.g. Magnusson et al. (1996), Frantzich (1998), DBHA (2004a), Hall and Watts (2008) and Yung (2008). Such methods are used directly in fire risk assessments, but they are also incorporated in various fire risk models such as the *CESARE-Risk*, *FIRECAM*, *FRAMEworks* and *CRISP* (Meacham, 2002).

However, many of these methods and models have difficulties with respect to modelling of interconnections between systems. Also, for example fault and event trees can only make binary representations of the states of the systems, which limits their potential accuracy. On the other hand, Bayesian networks can both incorporate an infinite number of states and they inherently consider conditional properties — i.e. the response of a system to the effects from other systems (Rausand, 2011). Thereby, more realistic and detailed analyses are possible by using Bayesian networks as a tool in a risk assessment process.

Additionally, the traditional fire risk assessment tools are mostly applied to studies of the effects of a fire. Thereby, few models covering the probability of fire occurrence are found in the literature, and even fewer models consider the entire risk picture including both probability of occurrence and fire event management and consequences (Hanea and Ale, 2009). Holický (2010) states that Bayesian networks can be effective tools in analysing this aspect of fire risk as many different interconnected variables influence the probability of fire occurrence.

Thus, Bayesian networks may improve fire risk analyses as they can better both describe the entire risk picture and incorporate conditional interactions between different systems. Thereby, Bayesian network models could provide a better basis for decision-making concerning building designs than the current methods. Thus, they can help solve the problems seen in deterministic performance-based fire safety design.

2.2 Existing Models

In academic circles, Bayesian networks have already been used in fire risk assessments. The literature shows that they have been used for example to model fire spread (Cheng and Hadjisophocleous, 2009, 2011) and to calculate risk to occupants (Hanea and Ale, 2009; Matellini et al., 2013). Additionally, more holistic models for calculating overall fire risk have been presented by Holický (2010) and De Sanctis et al. (2011). All these models are interesting to study in relation to the development of a framework for future use of Bayesian networks and, therefore, they will be examined in the following.

2.2.1 Fire Spread

Both a static and dynamic Bayesian network model for fire spread between compartments have been developed by Cheng and Hadjisophocleous (2009, 2011). The purpose of the two are the same; calculate the probability of fire spread from one compartment to another, however, the dynamic model considers the time dimension and calculates the expected time to ignition and time to flashover of the compartments. In this work, the newer dynamic model will be studied.

The model allows the fire to spread from one or more compartments to adjacent compartments both on the same floor and on the floor above. The model is claimed to be applicable to all types of buildings including high rise buildings, and it is based on specification of the compartments with regards to geometry, fuel, fire resistance etc. An interesting thing about the model is that the user gives some of the inputs to the model as probability distributions, thereby, the model can take probabilistic variations into account.

The model solely considers fire spread and does not couple the information to other fire risk aspects. Thus, interactions with other variables such as fire service operations or occupant behaviour is not taken into account. Therefore, the model may be used as input to a more thorough fire risk assessment, however, additional analyses are needed in order to describe the entire risk picture. Alternatively, the model can be used as input to or as a part of a larger Bayesian network model that considers more factors.

2.2.2 Risk to Occupants

Hanea and Ale (2009) have developed a Bayesian network model that considers the risk to occupants in a building on fire. The model considers three aspects of a building fire; the fire development, evacuation of occupants and the fire fighting actions. The model includes variables such as door width, fire growth rate, compartment area and the number of occupants. The relevant parameters are summed up in a RSET and an ASET node. These two nodes are used to calculate the output of the model, which is the percentage of occupants who can be expected to die during the fire.

Hanea et al. (2012) used the model to study the Schiphol Cell Complex fire, but found that the model could not be validated based on a single fire event. Still, Hanea et al. (2012) claim that the model can be used if the objective is not to give a fixed number of fatalities, but to compare different building and fire safety design options.

Another model that can be used to calculate risk to occupants in case of fire, is the model by Matellini et al. (2013). It considers fire development and human escape in dwelling fires. The model has two parts; the first deals with the initial fire development until detection and human reaction, and the second deals with evacuation of occupants and the actions of emergency services. The model can be used to assess the risk to persons depending on for example whether a smoke alarm is installed, the actions of the occupant upon detecting the fire and the characteristics of the dwelling.

From a risk perspective, the weakness of both the models by Hanea and Ale (2009) and Matellini et al. (2013) is that they only consider the consequences of a fire. The other part of the risk picture — the probability of occurrence — is not considered in the model at all. Thereby, these models can be used as an alternative or supplement to the tools currently used in deterministic practice such as CFD models and evacuation calculations, however, the full risk picture is not investigated. Nonetheless, developers of new models may find the models interesting as concepts for combining different variables into measures of ASET and RSET are presented.

2.2.3 Holistic Fire Risk Models

The models mentioned thus far have in common that they do not consider the probability of occurrence of a fire but, instead, they focus on the events after ignition. However, models with a more holistic approach — i.e. considering the entire risk picture as described by figure 1.2 on page 6 — is found in the literature, too.

A decision model based on a Bayesian network that considers both probability of fire occurrence and subsequent fire scenarios has been presented by Holický (2010). The objective of the model is to calculate the cost of fire safety measures compared to the safety level of the building in terms of injured persons and damage to the building.

In the model, the probability of fire occurrence is modelled as a fixed probability. Thus, the influences of different parameters on the particular building is not considered in the model and must be conducted separately. In general, the model is rather coarse compared to the other models described here, thus, the uncertainties in Holický's model will be larger, when the model is applied to a particular building as fewer parameters are used to describe it.

Another holistic fire risk calculation model has been presented by De Sanctis et al. (2011). The concepts of this model are similar to the ones of the model by Holický (2010) in many regards, however, the model by De Sanctis et al. (2011) considers several influential factors on fire occurrence. Thereby, the model treats this variable in a more specific way, allowing the model to better describe unique characteristics of the particular building under investigation. Also, the model by De Sanctis et al. (2011) can be further developed by introducing detailed sub-models such as models for fire spread or threat to occupants. Thereby, this model can be extended as methods, knowledge and data improve.

The model by De Sanctis et al. (2011) can supposedly evaluate the robustness and vulnerability of a building. De Sanctis et al. (2011) claim that the model can be used to calculate an economic optimum weighing the level of safety and the cost of the fire safety measures installed in the building. However, the model do not consider treatment of uncertainties in the analysis and, generally, the model makes some rather coarse assumptions. Also, it seems that De Sanctis et al. (2011) believe that a single, generic fire risk model can cover a large variety of buildings. However, it is thereby assumed that individual differences in building designs can be covered by a single model. Such a rationale can be questioned as this would introduce unnecessary uncertainties in the calculations similar to the ones seen in the model by Holický (2010).

Despite this, the model shows how a combination of dynamic and static Bayesian network sub-models can be combined to a tool that can describe the entire risk picture of a given building — and this may be used in the development of a new framework for application of Bayesian networks in fire safety engineering.

2.3 Preliminary Conclusions

The literature survey showed that Bayesian networks can be applied to the field of fire safety engineering with advantage compared to previous methods used for fire risk assessment. Thereby, the first question of this work has been answered: There is a large potential in using Bayesian networks in fire safety engineering compared to previous methods. Thus, the remainder of this work will be concentrated on how the method is best applied.

The models described in this chapter have been analysing fire risk with varying levels of detail, and they have described the total risk picture to different degrees. Thereby, the models show that Bayesian networks can be used as input to a larger and more traditional risk analysis, or they can be used to investigate the combined effect of different fire safety measures through a more holistic approach. However, none of the models described in this chapter has explicitly described uncertainty and, thereby, from a Bayesian perspective on risk, they fail to describe the risk to a fulfilling extent. Thus, there is room for improvement.

Exactly how the different aspects of the models can be used in the development of a framework for use of Bayesian networks in fire safety engineering will be described in chapter 5. But before those conclusions are made, it is investigated how Bayesian networks are applied in practice in fields of safety engineering with a longer tradition of using risk assessments — more specifically, how the TRANSIT model is used in assessment of road tunnel safety.

Chapter 3

TRANSIT and the Rogfast Tunnel

This chapter describes the TRANSIT model and the Rogfast project. The analysis of TRANSIT covers the architecture of the model, the key assumptions made, the background for some of the conditional probability tables and a deeper analysis of the accident modification factor (AMF) sub-model, which is a central concept in the model. Afterwards, the section concerning Rogfast will briefly describe the technical aspects of the tunnel, before the conclusions of the different risk assessment are presented and the risk-related challenges are discussed.

The objectives of the chapter are (i) to establish a basis for evaluation of TRANSIT, and (ii) to identify how methods and key parameters are used in the Bayesian network model in order to make basis for a comparison to building fire safety.

However, fundamental knowledge of road tunnel safety is needed in order to understand the reasoning behind TRANSIT and Rogfast. A summary of road tunnel safety challenges is given in the first section of this chapter, but a more thorough exposition is found in appendix B.

3.1 Introduction to Road Tunnel Safety

Road tunnels provide quick and easy routes for traffic that has to cross channels, seas, fjords and belts or to pass under mountains or cities. However, tunnels involve numerous safety challenges including how to prevent traffic accidents, tunnel fires and accidents with hazardous materials.

Generally, road tunnels are as safe or safer than similar open roads, however, the consequences of fires and accidents are often more severe in tunnels (Nævestad and Meyer, 2014). The accident rate differs through a tunnel; the rate is highest near the entrance and exit portals of the tunnel Hovd (1981). Tunnel fires are typically started by traffic accidents or technical failures (Nævestad and Meyer, 2014). Therefore, safety measures are concerned with prevention of accidents.

According to the Norwegian road tunnel guideline (NPRA, 2010), a risk analysis must be carried out for all road tunnels longer than 500 metres. The corresponding risk analysis guideline (NPRA, 2007) states that the risk analysis should identify unwanted or dangerous events, their causes and the possible consequences. In general, the parameters listed in table 3.1 have been identified as key to assess safety of road tunnels, and should be considered in any road tunnel risk assessment according to the European Parliament (2004). Additionally, the type of ventilation system, lighting in the tunnel, signs and information to tunnel users and installation of safety equipment such as fire extinguishers all impact the safety level of a tunnel (NPRA, 2010).

Table 3.1 shows that most of the parameters of concern in tunnel safety relate to accident prevention. This opposes what is seen in building fire safety, where focus often is on the effects of a fire as seen in table 1.1 on page 5. Hence, a rough comparison to the fire safety concept trees in NFPA 550 (2012) shows that engineers working with road tunnel safety focus on prevention of unwanted incidents, whereas fire safety engineers primarily focus on mitigation of effects. This does not hinder a comparison of the use of Bayesian network models in the two fields of engineering as the branches of the safety concept tree are equally important, however, it indicates that models cannot be expected to be directly transferable from one field to the other given the current practices. With this in mind, the presentation of TRANSIT and Rogfast can commence.

3.2 The TRANSIT Model

As mentioned, TRANSIT is a road tunnel risk assessment tool based on Bayesian networks. TRANSIT is an abbreviation of "*T*unnel *R*isk *AN*alysis on a *S*egmental

Table 3.1: Parameters that must be considered in a road tunnel risk assessment according to the European directive 2004/54/EC (European Parliament, 2004).

• Tunnel length • Number of tunnel tubes • Number of traffic lanes • Cross sectional geometry • Vertical and horizontal alignment • Type of construction • Uni-directional or bi-directional traffic • Traffic volume per tube (and time distribution) • Risk of congestion (daily/seasonal)	• Access time for emergency services • Presence and percentage of heavy goods vehicles • Presence, percentage and type of dangerous goods traffic • Characteristics of the access roads • Lane width • Speed limit • Geographical and meteorological environment

basis by using *I*nfluence diagram *T*echnique". It is the result of a research programme partly funded by the Norwegian Public Road Administration (NPRA) and the Federal Road Office of Switzerland (FEDRO) and conducted by a consortium consisting of Matrisk GmbH and HOJ Consulting GmbH (Schubert et al., 2012a).

TRANSIT is designed with five key characteristics in mind. The five characteristics and how the developers seek to achieve them are described in the following list (Schubert et al., 2012a).

- Focused: The model should support relevant decisions concerning planning, operation and maintenance.
- Innovative: The model should include the latest research and technology and represent the best practice in road tunnel safety.
- Consistent: The model should be based on Bayesian networks in order to consistently incorporate updates of information such as data and models.
- Transparent: The model should be transparent in order to encourage refinements and improvements. Also, the limitations of the model should be clearly identifiable.
- Actionable: The model should be implemented in a way that makes it easy to use.

3.2.1 Aim and Applications

According to the developers, Schubert et al. (2012a), TRANSIT is applicable to all European road tunnels, however, the model has been developed with special considerations to tunnels relevant in Norway and Switzerland. Furthermore, Schubert et al. (2012a) claim that TRANSIT is a "best practice" for road tunnel risk assessment and is based on the recommendations by the European Parliament (2004), thus incorporating the parameters described in table 3.1 on page 18.

TRANSIT is designed to cover all three main risk contributors in road tunnels, namely traffic accidents, fires and accidents involving hazardous materials — cf. appendix B. According to Schubert et al. (2012b), this makes TRANSIT unique compared to most other risk assessment tools used for road tunnels, as other models fail to cover all three aspects.

Technically, the model is applicable to a wide variety of tunnels, however, the input options give some limitations to the use. Such limitations include that the AADT must be between 300 and 60000, the gradient between 0 % and 10 % and the share of HGVs between 1 % and 26 %. Additionally, the current version is only applicable to tunnels in Norway or Switzerland, if not all tunnel parameters are known as prior probability tables on the input parameters have only been developed for these two countries.

3.2.2 Architecture of TRANSIT

The user interface in TRANSIT is developed in a Microsoft Excel 2007 environment. Here, the user specifies in which country the tunnel is located, which is relevant for the prior probabilities of the different parameters. The user also specifies the total length and the number of different homogeneous tunnel segments in which the risk can be assumed uniformly distributed — an example is seen in figure 3.1. Additionally, the user must specify the type of ventilation system, whether a monitoring system is installed, what the compensation cost for injuries and fatalities are, and the criteria concerning the acceptable rate of accidents and fatalities (Schubert et al., 2012a).

The segments are assigned their different characteristics. Five different types of tunnel zones are available plus a zone 50 metres before entering and after leaving the tunnel. The zones are defined based on the placement in the tunnel and are used to calculate the accident rates of the zones based on the knowledge about variation in the rates described in section 3.1 and in appendix B. However, the data foundation for TRANSIT does not describe exit zones, which is why assumptions are made on these based on the conditions in the entrance zones. Apart from the placement in the tunnel, the segments may vary with respect to length, position in the tunnel, entrance or exit ramps, traffic volume, number of lanes, horizontal curvature etc. (Schubert et al., 2012a).

The relevant input parameters from each segment are transferred to the two Bayesian network models in TRANSIT — one is for calculating accident and fire rates (called network A in this work), whereas the other is for investigations into accidents involving hazardous materials (called network B in this work). Despite their different applications, the basic structure of the two models are the same.

A number of key performance indicators (KPIs) are used as input nodes. They represent the various observable tunnel characteristics such as traffic volume, types of systems installed as well as other tunnel design parameters. The KPIs are linked to non-observable indicator (NOI) nodes such as chances of successful

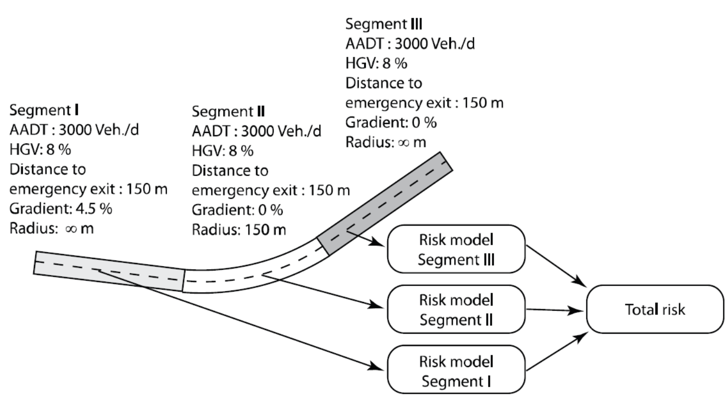


Figure 3.1: A tunnel consisting of three segments with varying risk levels (Schubert et al., 2012a).

evacuation, vehicles per kilometre, thermal load and fire severity, i.e. parameters that are directly derived from for example the traffic data. Further, the NOIs are linked to outcome nodes. Additionally, network A has incorporated so called logical non-observable indicator (LNOI) nodes, which serves as distribution factors for the fatality rate etc. (Schubert et al., 2012a). The two networks in TRANSIT are seen in appendix C.

In total, network A has 38 nodes and network B has 29 nodes. The numbers of KPI, NOI, LNOI and outcome nodes in the two networks are seen in table 3.2. The numbers show that the KPIs incorporated in the two networks are slightly different. 11 of the KPIs are recurring in both networks, whereas the rest is claimed to be relevant only for one of the two scenarios (Schubert et al., 2012a). Thus, in total 22 different KPIs are used to describe a tunnel segment. Additionally, table 3.2 shows that the number of directed edges in the two differs. The ratio between edges and nodes are slightly higher in network A, which indicates that the nodes here are more interconnected.

Network A has two main parts — calculations concerning accidents and calculations concerning fires. The accident part calculates the mean values of the accident rate and the fatality and injury rates due to accidents. The mean values are expressed in terms of accidents, fatalities or injuries per vehicle per kilometre.

A key parameter used in the calculation of these mean values is the accident modification factor (AMF), which is a LNOI node. This parameter is a positive number that describes the number of accidents in the tunnel under investigation compared to the accident rate on the entire road tunnel network in the given country. Thus, an AMF value of 1 means that the rate in the tunnel segment is equal to the rate on the entire road tunnel network (Schubert et al., 2012a). The AMF model is further described in section 3.2.4.

The other part of network A, the part concerning the fire related parameters has input from the mean value of the accident rate as well as variables concerning traffic conditions, type of ventilation system and parameters related to evacuation. The purpose of this part is to express the injury and fatality rates due to fire. These rates are calculated based on the evacuation conditions, the number of vehicles per kilometre and the severity of the fire. The conditional probability tables for the number of injuries and fatalities due to fire are constructed from expert judgements based on observations from past tunnel fires (Schubert et al., 2012a).

Table 3.2: The number of nodes and edges in the two Bayesian networks in TRANSIT.

	Network A	**Network B**
KPI	17	16
NOI	12	7
LNOI	4	0
Outcome	5	6
Total, nodes	38	29
Total, edges	59	41

Network B can be seen as divided in three main parts — toxic emission, explosion and pool fire[1]. All three parts are based on the node describing the probability of occurrence of a dangerous goods event as well as a list of parameters related to the different scenarios. The dangerous goods event node is based on a traffic volume time-variation curve and the tunnel class based on the classes described by OECD (2001) as seen in table B.1 on page 82. The outputs from this network are injury and fatality rates from events with each of the three types of hazardous materials (Schubert et al., 2012a).

The final output of TRANSIT is the expected values of the injury rate, the fatality rate, the accident rate, the fire rate etc. These results are both provided for the entire tunnel as average values and for the individual tunnel segments.

In the rest of this work, the main focus will be on network A, i.e. the network calculating the accident and fire rates, as this is considered to be most relevant to risk assessment in the building fire safety industry.

3.2.3 Key Assumptions

A number of assumptions is incorporated in TRANSIT. The foundation of the model is the assumptions that a tunnel can be split into segments with a homogeneous risk level and that these segments can be described by a number of specific parameters (KPIs). It is also assumed that all road tunnels have only seven different types of tunnel segments and four different types of intersections. Additionally, it is a key assumption that all the different road tunnels can be described by the same generic data and that they can be analysed using one model — at least to a certain extent[2] (Schubert et al., 2012a).

The TRANSIT manual defines risk as the expected value of the probability of an event times the potential consequence as given in equation (1.2) on page 7 (Schubert et al., 2012a) — hence, a Frequentist perspective is adopted. This is expressed through the outputs of the model as they are all given in mean values for the different segments and differs from the Bayesian definition from Aven (2010) as the uncertainty of the analysis is not inherent in the results.

Another assumption is that tunnel design in different countries only differs in terms of the prior probabilities. Thereby, TRANSIT assumes that the parameters contained in the model are sufficient to describe all the differences in tunnel construction practices in European countries.

With regards to application of the model, the conceptual assumption is that decision makers are willing to make decisions based on generic, thus not project specific, prior probabilities in cases where the tunnel is not thoroughly described, for example early in the design phase.

[1] These three types of incidents are typically considered in road tunnel risk assessment concerning hazardous materials — cf. appendix B.

[2] The TRANSIT manual has some reservations with concern to particular parameters and special conditions.

3.2.3.1 Prior Probabilities

In addition to the more overall assumptions, TRANSIT also makes different assumptions regarding the prior and conditional probability tables used in cases, where not all tunnel characteristics are known. The prior probabilities are based on historical data, expert judgement, various assumptions, approximations and derivations (Schubert et al., 2012a). Here, the reasoning behind the prior distributions for three selected parameters is presented in order to give a picture of the underlying assumptions and the scientific base of the model.

First, there are six different time-variation curves in TRANSIT. They represent roads with different combinations of peaks in the morning and afternoon. The prior probabilities are based on the Swiss standard SN 640 005a and a German study. The prior probabilities for Norway are assumed to be the mean value of the values from Switzerland and Germany, however, the reasoning behind this choice is not described in the manual (Schubert et al., 2012a).

Second, the prior probability for the fraction of heavy goods vehicles (HGVs) in the tunnel is based on statistics for HGVs on open roads in Switzerland and is defined equally in both Norway and Switzerland. The impact of HGVs on the accident rate is based on research conducted by OECD and the World Road Association (PIARC) showing that the presence of HGVs increases the accident rate. The accident rate is assumed to be linear dependant on the fraction of HGVs and, furthermore, statistics from the Swiss Federal Statistical Office are used.

TRANSIT assumes that the prior probabilities in Switzerland and Norway are equal. Schubert et al. (2012a) have not documented how the distribution is in Norway nor is it documented whether it is reasonable to assume the same prior probability for Switzerland and Norway. Additionally, TRANSIT does not explicitly consider buses in the tunnel. Potential bus passengers are addressed in the variables concerning the number of people exposed to fires etc., however, the manual states that additional analyses are needed if TRANSIT is to be used in tunnels, where a large number of buses are to be expected (Schubert et al., 2012a).

Third, the prior probability table for the tunnel gradient is based on data from Switzerland. Similar to the prior probability of the fraction of HGVs, the prior probability for Switzerland and Norway are assumed equal. However, the reasoning behind this is not documented in the manual (Schubert et al., 2012a).

3.2.4 Analysis of the AMF Node

A key concept and a kernel node in TRANSIT is the accident modification factor (AMF) mentioned in section 3.2.2. This node influences the accident rate and thereby the fire, the fatality and the injury rates. This section will analyse this parameter as the idea of a central factor that governs the occurrence of a key event may be applicable to Bayesian networks concerned with building fire safety.

The AMF is used to combine the influence of relevant tunnel parameters on the accident rate. Data for all of the combinations of the parameters do not exists, which is why a comparison to a "standard value" is deemed the most suitable method to evaluate the different scenarios and the related amount of information

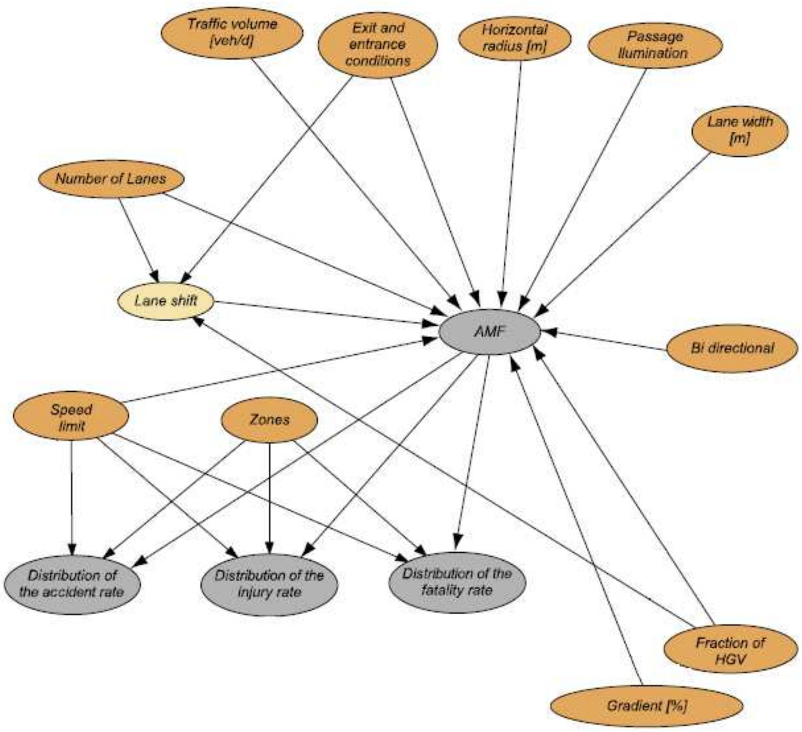
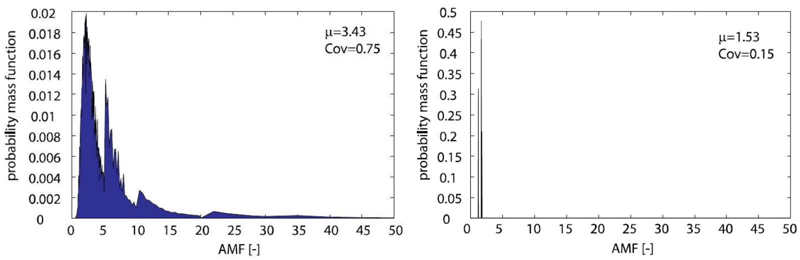


Figure 3.2: The Markov blanket for the accident modification factor (AMF). The figure is based on the full network by Schubert et al. (2012a) seen in appendix C.

(Schubert et al., 2012a). Thereby, the AMF is the child of 11 nodes representing different relevant parameters such as lane width, entrance and exit conditions and traffic volume.

Each of the parents of the AMF node describes an accident modification factor related only to the given parameter. The combined accident modification factor, i.e. the AMF node, is calculated by multiplying all the sub-AMFs of all the parents. Despite this, the AMF node is not a single value, but a probability distribution of the AMF for the tunnel segment in question. Therefore, the probability table for the AMF node contains 1,344,208,860,336,380 ($\approx 1.3 \cdot 10^{15}$) cells due to the amount of states of the different parent nodes (Schubert et al., 2012a).

The Markov blanket for the AMF is seen in figure 3.2. The Markov blanket contains the nodes that influences the AMF and consists of 15 nodes. In this case, including the distributions of the accident, injury and fatality rates, and thereby the "zones" node, is mainly theoretical as evidence is unlikely to be inserted to these nodes; conducting a risk analysis would be rather redundant, if such evidence existed. Furthermore, it should be noted that the node "Lane shift" is based on the time variation curve of the traffic volume and the hour of the day as seen in the full network in appendix C.



(a) No information about the KPIs. (b) Full information about the KPIs.

Figure 3.3: The probability density function of the AMF with varying amount of evidence inserted. The coefficient of variation (CoV) of the distribution depends on the amount of information available (Schubert et al., 2012a).

Figure 3.3 shows the distribution of the AMF node with no information inserted in the KPIs and with information inserted in all of the KPIs, respectively. The graphs show that the AMF is highly dependant on the available amount of information and that the probability density functions are quite irregular with several spikes in the data. It is also seen that the coefficient of variation, i.e. the standard deviation divided by the mean value, differs with 0.60 between the two states. As the AMF is a central parameter in the network, the difference shows that the uncertainties in the final results are highly dependant on the amount of information inserted. But even with all information inserted, some variation of the AMF is seen, thus, the final results in terms of expected values contain some uncertainty even without including the uncertainty in the prior probabilities and in the analysis in general.

To summarise, TRANSIT splits a tunnel in different segments with a homogeneous risk profile and calculates the AMF for each segment. The AMF is a central variable in TRANSIT, thus it has a large impact on the the final result of the model. There is some uncertainty related to the AMF even with all information available, however, TRANSIT does not address these uncertainties in the final results.

3.3 The Rogfast Project

In order to evaluate the utility of TRANSIT in practice, the model is evaluated on the potential and actual use in the Rogfast tunnel project. In this section, the Rogfast tunnel project will be described.

Rogfast will be a road tunnel crossing the Boknafjord and Kvitsøyfjord north of the city of Stavanger in south-western Norway as seen in figure 3.4. As mentioned, it is relevant for this work as it is a complex and state of the art project and, thus, suitable for testing the applicability and limits of TRANSIT.

The name Rogfast is a abbreviation of "Rogaland fast forbindelse" meaning "Rogaland fixed link" and will be part of the European road link E39, which runs from Aalborg in Denmark to Trondheim in Norway and links the major cities of south-western Norway. The developer of the tunnel is the Norwegian Public Roads Ad-

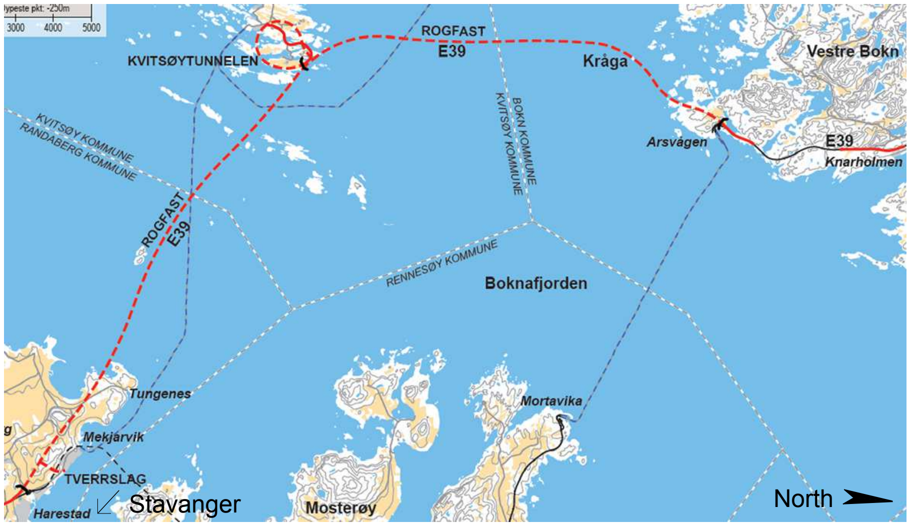


Figure 3.4: Map showing the projected path of Rogfast north of the city of Stavanger (NPRA, 2014).

ministration (NPRA). The tunnel will replace the current ferry link and, upon completion, the tunnel will cut travelling time across the fjord by approximately 40 minutes (NPRA, 2014).

The tunnel was preferred to a solution, where the ferry connection were upgraded, based on a socio-economic analysis by NPRA (2002). Here, the analysis found that an upgraded ferry connection would have no effect on any of the parameters investigated. However, both the transport quality and the regional economic development of both the housing and the labour markets would benefit greatly from the tunnel solution. It was concluded that the downside of the tunnel project is that it will result in extensive negative consequences on the landscape in some areas.

In addition to the main tunnel, the project also includes a 4 km long tunnel arm to the island of Kvitsøy implying a sub-sea intersection approximately 15 km into the tunnel from the southern entrance (NPRA, 2014). Figure 3.4 shows a map of the area and the location of the tunnel. The map shows that the tunnel starts well inland on both sides. This is necessary in order to avoid too steep gradients due to the depth of the fjord. The length of the tunnel arm to Kvitsøy is mainly due to the depth of the main tunnel.

The company Norconsult will be doing the the detailed design work on the project, which is scheduled to begin in the summer of 2014. Tunnelling is scheduled to start in 2015 and, according to the plan, the tunnel will open in 2022-2023. The total price of the project is estimated to be 13.8 billion NOK or approximately 1.65 billion EUR (NPRA, 2014).

3.3.1 Description of the Tunnel

Now, the more technical aspects of the tunnel will be presented both for the main tunnel and for the tunnel arm to Kvitsøy. The information in this section is based on the scheme design described by Hokstad et al. (2012) in the SINTEF/COWI risk and vulnerability analysis. The presented specifications do not include the recommended alterations to the original design suggested in the report.

3.3.1.1 Main Tunnel

The main tunnel will be approximately 25.5 km long and will consist of two parallel tunnel tubes, which each will have two lanes of traffic. The lowest point in the tunnel will be 390 metres below sea level, but the gradient will vary some through the tunnel. The maximum gradient in the main tunnel will be 7 %, which is the maximum allowed for this tunnel according to the Norwegian tunnel guideline (NPRA, 2010).

The annual average daily traffic (AADT), which is a measure of the traffic volume, is expected to be 13,000 vehicles 20 years after opening. The share of HGVs is expected to be 15 %. The tunnel will be a toll road, and the AADT will be regulated to the desired level by adjusting the price. Originally, the speed limit in the main tunnel is suggested to be 90 km/h.

Actually, the Norwegian tunnel guideline (NPRA, 2010) is only valid for tunnels with a length up to 10 km. Therefore, it is not directly applicable to the Rogfast tunnel. In order to negate this, the main tunnel is assigned to tunnel class F despite that the tunnel would be in class E, if only the AADT was considered. The prescriptive safety measures for tunnel class F includes less distance between emergency lay-bys, a higher design fire load and a higher maximum ventilation rate compared to class E.

Due to the tunnel class, the main tunnel tubes will have emergency exits linking the two tunnel tubes for each 250 metres, which is also the distance between emergency lay-bys. The shoulder will have emergency lighting in order to ease evacuation. In addition to the emergency exits, there will be drivable cross connections for each 1500 metres, which can be used during maintenance or emergency service operations. Furthermore, emergency stations equipped with a direct emergency telephone to the operations centre as well as two fire extinguishers will be placed for each 125 metres. The tunnel entrances will be equipped with stop lights and automatic traffic gates in order to stop the traffic in case of emergencies. Tunnel class F imply that the entire tunnel has video surveillance with automatic incident registration.

A longitudinal fire ventilation system will be installed that will push smoke gases in the traffic direction. The system will be dimensioned based on a 100 MW fire. Tunnel equipment will be designed to resist a fire equivalent to a RWS fire curve[3] for 2 hours.

[3] The Rijkswaterstaat (RWS) curve is a fire curve developed by Dutch authorities for enclosed spaces such as tunnels.

3.3.1.2 Kvitsøy Tunnel

The 4 km tunnel arm to Kvitsøy will have only one tunnel tube and, thus, bi-directional traffic. In most of the tunnel, the gradient will be 7 %, which, like the main tunnel, is the maximum allowed for this tunnel. The lowest point in the tunnel is at the intersection with the main tunnel, which is 260 metres below sea level.

The AADT for this tunnel 20 years after opening is expected to be 900 and, like the main tunnel, the share of HGVs is expected to be 15 %. The speed limit in this tunnel is suggested to be 80 km/h.

The most recent public available drawings of the intersection between the Kvitsøy tunnel and the main tunnel show that the intersection will be grade separated using four ramps in order to optimise traffic flow in the main tunnel (NPRA, 2014). However, the traffic to and from the ramps to the Kvitsøy tunnel will be merged in two separate roundabouts, which disregards the recommendation to avoid intersections in tunnels stated in the Norwegian tunnel guideline (NPRA, 2010).

The Kvitsøy tunnel has not been assigned a tunnel class due to the special circumstances and deviations from the tunnel guideline. However, it is in many ways treated similar to the main tunnel as it is part of the overall system.

3.3.2 Risk Assessments

In this section, the main points from the four different risk assessments that have been made for Rogfast at the present moment will be presented. These include two different risk and vulnerability studies made by Norconsult (Dahle et al., 2006) and SINTEF/COWI (Hokstad et al., 2012), respectively, a contingency analysis made by NPRA (Hofseth, 2012) and a risk analysis of HGVs in Rogfast made by HOJ Consulting (Høj, 2013).

Only the work by Høj (2013) incorporate calculations made with TRANSIT, however, the others are described in order to establish a knowledge base for evaluating TRANSIT.

3.3.2.1 Risk and Vulnerability Analyses

The risk and vulnerability analysis by Norconsult (Dahle et al., 2006) is not up to date as it was made in an early stage of the project. However, some of the conclusions are still relevant and, therefore, it has been included here. Some of the goals of the analysis are (i) to identify possible solutions to the intersection with the Kvitsøy tunnel, (ii) to assess the risk in relation to the proposed gradients as well as (iii) to clarify key requisites in the project.

The analysis by Dahle et al. (2006) is based on calculations in TUSI, which is a Norwegian road tunnel risk assessment tool from the 1980s and is based on accident databases and statistical models (NPRA, 2007). These calculations show that the accident rate in Rogfast will be significantly lower than the average Norwegian sub-sea road tunnel. A slightly lower gradient was not found to reduce the risk significantly. The main contributions to the risk level come from the length of the tunnel and the high share of HGVs. Also, the analysis found that a large number of vehicle breakdowns can be expected. Therefore, it recommends that a system for handling these incidents is developed. Furthermore, Dahle et al. (2006) recommend that the intersection between the main and Kvitsøy tunnels are grade separated. Additionally, a list of recommended safety features are presented.

Dahle et al. (2006) conclude that Rogfast will be safer than the current system for crossing the fjords, which includes two smaller tunnels with high gradients as well as the ferry link mentioned in the introduction to this section.

The more recent risk and vulnerability analysis made by SINTEF/COWI (Hokstad et al., 2012) lists more specific risk reducing measures. Here, the risk level for both normal and deviating operation mode as well as risks in the construction phase are considered. It is a coarse analysis following the guideline by NPRA (2007) and it covers design of both tunnel geometry, installations and systems as well as measures for adequate rescue service intervention and operation. The risk level in the main tunnel is evaluated by calculations using the TUSI model by comparing Rogfast to an imaginary reference tunnel, which is within the limits of the Norwegian road tunnel guideline by NPRA (2010).

Hokstad et al. (2012) recommend that the distance between emergency exits are decreased to 125 metres, that the fire ventilation system is designed based on a 200 MW fire and that there are limitations on the transportation of hazardous materials. Furthermore, it is found that crawler lanes does not decrease the risk significantly in normal operation mode, however, it is found to be beneficial with concern to the case, where one tube is closed due to maintenance, accidents etc.

The analysis by Hokstad et al. (2012) also assesses three different solutions for the intersection between the Kvitsøy tunnel and the main tunnel. The alternatives are two two-level intersections — one with two roundabouts and one with a diamond intersection — and a three-level intersection with direct ramps to and from each direction of traffic. It is found that a three-level intersection would be most beneficial with respect to smoke management and would yield fewer traffic accidents, whereas, the solution with roundabouts would allow drivers to make u-turns. According to Hokstad et al. (2012), traffic accidents in roundabouts have low consequences, which partly negates the higher accident rate. The diamond intersection solution makes it easy to convert the tunnel to bi-directional traffic in case of maintenance, accidents etc., which is the main advantage of it.

The analysis concludes that the most efficient solution with regards to smoke management would be a combination of a three-level intersection and two tubes with bi-directional traffic in the Kvitsøy tunnel in order to completely separate the two main tubes, thereby containing smoke in one main tunnel tube. However, this solution is found to be very costly and problematic with concern to traffic flow at the Kvitsøy tunnel portal.

With respect to emergency service operations in case of accidents, Hokstad et al. (2012) suggest different measures such as turning areas, active smoke barriers at the intersection, construction of helipads as well as establishment of a new traffic control centre.

3.3.2.2 Contingency Analysis

Another aspect of the risk picture has been studied by Hofseth (2012), who conducted a contingency analysis for Rogfast on behalf of the NPRA. The purpose was to design the safety systems in the tunnel to meet the needs of the emergency service and to dimension the emergency service in the surrounding area, enabling it to cope with the possible accident scenarios.

The analysis emphasises the challenge with operations due to the length of the tunnel, which both makes it unlikely that burning vehicles can continue out of the tunnel, increases the intervention time of the emergency service as well as complicates evacuation of tunnel users (Hofseth, 2012).

Hofseth (2012) recommends that the emergency service receives funding for new equipment and extended training. Furthermore, fire stations could be relocated in order to decrease response time. Alternatively or supplemental, a first responder service under the traffic control centre could be established. Such a service should primarily prevent escalation of accidents by quickly removing stranded vehicles, dropped cargo etc. as the fire frequency is expected to be rather low with few incidents per year (Hofseth, 2012).

3.3.2.3 Risk Analysis of HGVs

The last risk assessment investigates the effects of HGVs on the overall risk level in the tunnel and has been conducted by Høj (2013) from HOJ Consulting. This assessment was conducted in order to further investigate the results from the risk and vulnerability analysis by Hokstad et al. (2012) stating that an increase of HGVs from 15 % to 25 % would increase the frequency of fires by 45 % indicating that this parameter has a large impact on the final conclusion. The goal of the analysis was to determine whether the gradient in the main tunnel should be limited to 5 % leading to a 1.5 km longer tunnel in order to mitigate the fire risk.

The analysis is mainly qualitative and based on a hazard identification (HAZID) meeting, however, a model for the effect of the gradient on the fire modification factor (FMF), which corresponds to the accident modification factor (AMF), is presented. The model is based on the model used in TRANSIT to calculate the impact of the gradient. As expected, the model shows that a lower gradient will result in fewer fires.

Furthermore, preliminary calculations using TRANSIT were conducted for four different designs: (i) the original design described in section 3.3.1, (ii) the original tunnel with a speed limit of 80 km/h, (iii) the original tunnel, where exposed sections have a lower speed limit and restrictions on overtaking, and (iv) the original tunnel with a speed limit of 80 km/h and a maximum gradient of 5 %. The calculations did not include the Kvitsøy tunnel and various assumptions with regards to the safety systems in the tunnel were made (Høj, 2013). It is unclear to what extent the entrance and exit ramps are included in the analysis.

Based on the results of the original design, it was found that the average fatality rate will be slightly lower than on the average road network in Norway. Therefore, Høj (2013) concludes that additional safety measures should be considered from a perspective of the ALARP principle[4].

The second design solution was found to have a large impact on the accident rate, however, it had little impact on the fire rate. Høj (2013) found that the third design would yield an overall fatality rate similar to that of the best roads in Norway. On average, there would occur more than four fires per year. In total, he found that 11.4 incidents per year can be expected with the third design.

The fourth solution would yield a 18.2 % drop in the fire rate for HGVs in spite of the lengthened tunnel. Also, the fatality rate due to fires would decrease. However, Høj (2013) found that the overall fatality rate is dominated by the rate of fatalities due to accidents. Therefore, the fourth design would only slightly decrease the overall fatality rate.

The analysis concludes that a gradient limited to 5 % would not decrease the risk significantly according to the ALARP principle. Therefore, this proposition was not recommended. However, based on the qualitative part of the analysis, several measures were suggested including lowering speed limits, prohibition on HGVs in the fast lane and a requirement for retarders (Høj, 2013).

3.3.3 Challenges

The risk analyses show that the main challenges in the Rogfast project are related to the length and depth of the tunnel. This applies both to the probability of occurrence of accidents and fires as well as the systems and rescue operations designed to mitigate incidents. Also, the high share of HGVs is an important risk contributor.

Additionally, the sub-sea intersection poses a challenge as little data and knowledge exist for such a structure — intersections in tunnels are generally advised against by NPRA (2010). The challenge is related both to the analysis of potential traffic accidents and to the smoke management around the intersection.

The risk analyses of Rogfast present lists of safety measures that would improve safety, however, the original design of the tunnel is more or less found to be acceptable with exception of the distance between emergency exits and the speed limit.

A fundamental challenge in the Rogfast project is how to assess the risk level as the project is state of the art meaning that historical observations for such a tunnel do not exist. Bjelland and Aven (2013) question this aspect of the risk analyses and find that the Rogfast has been treated similar to standard road tunnels — e.g. standard incidents are considered in the analyses, but potential new types of incidents are not discussed. Also, application of models such as TUSI, which are based on statistical data, is found to be rather meaningless as the statistics are taken from tunnels with different premises.

Bjelland and Aven (2013) argue that it would be more fitting if the risk analyses focused on the unique characteristics of the Rogfast project instead of using only

[4] ALARP is an abbreviation of As Low As Reasonably Practicable and is a method to determine whether a safety measure should be implemented based on cost-benefit analysis (Rausand, 2011).

historical knowledge and introducing an imaginary reference tunnel as done by Hokstad et al. (2012). Additionally, Bjelland and Aven (2013) find it contradicting that the risk analyses on on side conclude that Rogfast will be safer than other tunnels, but simultaneously argue that further risk-reducing measures must be implemented. Finally, Bjelland and Aven (2013) state that the uncertainties implicit in the vast amount of assumptions are not treated to a satisfactory extent, and they suggest that focus is shifted to the background knowledge of road tunnels in order to describe the uncertainties better.

Thus, the challenges in the project relates to the physical uniqueness of the tunnel, but also to the conceptual approach to the analyses due to the novelty of the project. The challenges prove that the tunnel is non-standard, thereby making the project well-suited for a test of the limitations of TRANSIT.

3.4 Preliminary Conclusions

This chapter has described the TRANSIT model and the Rogfast project. It was found that TRANSIT is a rigid model based on statistical data, models and expert opinions with several assumptions. The model primarily focuses on variables concerned with preventing accidents in line with the recommendations in directive 2004/54/EC (European Parliament, 2004). Thereby, the model has another focus than typical fire risk models, which are more concerned with variables concerning management of fire events.

The Rogfast tunnel was found to pose several challenges — both with regards to the technical systems and to the concepts on how to analyse the safety level of the tunnel. These challenges was found to be relevant for testing the limitations of TRANSIT.

The next chapter will evaluate TRANSIT and analyse both the potential and actual use of the model in projects like Rogfast.

Chapter 4

Evaluation of TRANSIT

Based on the information found in the previous chapter, it is now time to evaluate TRANSIT with regards to both the general assumptions and the validity of the model. The first part of the evaluation will consider TRANSIT from a general perspective on risk and tunnel safety. Afterwards, the quality of results from TRANSIT in complex and non-standard projects will be assessed based on the Rogfast project. The findings of this chapter will be used as input to the framework for application of Bayesian network models in building fire safety.

4.1 TRANSIT in General

The general evaluation of TRANSIT considers the performance goals set up by the developers, how uncertainties are treated in the model, how a rigid model like TRANSIT performs in a design process and more.

4.1.1 Performance Goals

A natural way to start an evaluation of TRANSIT is to assess whether the five performance goals set up by the developers are met — to restate, the performance goals were that TRANSIT should be focused, innovative, consistent, transparent and actionable.

Borg et al. (2014) found that TRANSIT is focused in the terms of the developers, however, they argue that the standardised way of treating problems in the model is not necessarily meaningful for complex problems. Thereby, the standardised method of TRANSIT may turn focus towards standard problems instead of identifying unique challenges to the project at hand. This will be discussed further in section 4.2 as this could be a problem in the Rogfast project.

The goal to be innovative is found to be met as the Bayesian network model provides a new approach to the challenges in assessing risk in road tunnels, at any rate compared to past methods in Norway.

TRANSIT is considered consistent by the developers as a systematic methodology is used to update and handle new information (Schubert et al., 2012a). This can hardly be argued as the mathematical theory on Bayesian network is solid. However, Borg et al. (2014) state that the consistency is not a goal itself as one can be both consistently right or wrong. For instance, the expected value of parameters may be used consistently, however, it may not be rewarding as it discounts the uncertainty in the analysis. Additionally, Borg et al. (2014) found that TRANSIT cannot incorporate expert judgement on the conditional probabilities for input parameters, thus, there is no consistent methodology for updating TRANSIT, if non-standard inputs are preferred.

Borg et al. (2014) found that the documentation generally makes TRANSIT transparent, however, they state that the vast amount of variables makes the model complex and, hence, the user is required to have a lot of background knowledge in order to apply the model correctly.

The present study finds that the documentation only provides basic information and that detailed documentation lacks for some variables as seen in the previous chapter. The problems concern the use of the expert opinions as a base for some of the probability tables without explanation and the lack of elaboration on the foundation of some of the sub-models and assumptions. Thus, the uncertainties of the model and individual variables are poorly described. The uncertainty of the variables must be communicated in order for the user to assess whether the model can be reasonably applied in a given project. An improvement of the documentation would be beneficial for most stakeholders as it would provide a better information basis for decisions and fails to describe key assumptions. Thus, from this perspective, the documentation is rather deficient. On this basis, it can be argued whether the model can be considered transparent.

TRANSIT is considered actionable by Borg et al. (2014) as the model is easy to use and run. However, Borg et al. (2014) are concerned that this fact is also a Achilles heel for the model as risk analysts over time may conduct the calculation somewhat automated. Thereby, the recommendation that users should have good knowledge and experience in risk analysis and tunnel safety may be negated as the studied projects may be seen only from within the limits of TRANSIT.

A Bayesian network model for use in fire safety engineering should be evaluated on similar performance goals and could learn from the criticism of TRANSIT in this regard.

4.1.2 Rigour versus Relevance

The fact that users are limited in their use of TRANSIT to already defined states of the different parameters and that altered probability tables or new variables cannot be implemented by users makes the model rather rigid compared to many other techniques used for risk analyses — e.g. procedures like HAZOP and FMECA (Rausand, 2011). The rigidity has some advantages as the same analysis is applied to all tunnels, thereby it provides easily comparable results. However, potentially it also limits the use of TRANSIT as the uniqueness of complex problems may not be given the required consideration.

Borg et al. (2014) state that TRANSIT assumes that all relevant information in a given project can be incorporated into a Bayesian network structure, which may not be the case — e.g. TRANSIT has no way to identify new accident modes and analysts have no way to control, which scenarios are considered and emphasised. Also, TRANSIT does not incorporate the risk of deliberate actions to cause harm. This accident mode may not be easily described in a quantitative model, however, it must be included as part of the risk analysis in order to cover the entire risk picture. Thus, when TRANSIT claims to be a holistic model, decision makers might overlook this aspect of the risk assessment.

Schön (1983) describes how many practitioners uses "silent" knowledge such as intuition, experience and commitment when dealing with complex problems. In TRANSIT, an effort is made to standardise this knowledge and put it on formulas, which in Schön's perspective can be problematic as it hinders innovation and application of common sense. Also, Schön (1983) argues that practitioners often uses their silent knowledge and their capacity to reflect-in-action to manage complex problems. This is difficult in TRANSIT as it is a rigid model, where special considerations cannot be implemented directly.

Further, Schön (1983) describes a dilemma between rigour and relevance — is rigid academic knowledge valid in contexts, where unstudied issues are seen? Schön figuratively describes this problem as two different terrains; a dry highland and a muddy lowland. In the highland, rigid academic knowledge can be applied with little thought as problems are either simple or well-understood and there are few sources of uncertainty. On the contrary, the academic knowledge has limited value in itself in the muddy lowland, where complex problems exists, which cannot be looked upon isolated as they are entangled in and influenced by both the surrounding environment, the stakeholders and large uncertainties. Practitioners, who operate in the lowland, may try to use the techniques developed in the highlands to escape a mud pool and navigate the landscape, however, at some point they will get stuck in another mud pool, and they will have to rethink their strategy. Metaphorically, TRANSIT can be said to be developed in the highland and the model has to stand the test in the mud, when it is applied to complex or "muddy" projects like Rogfast. The model might solve some problems, but other may appear.

However, Schön (1983) argues that the rigour-relevance dilemma should not be used to view problems as being in either the highland or the lowland. Instead, he argues that the dilemma should be used to realise that science is not static, but is a process where scientists constantly tries to minimize uncertainties in the methods they use and knowledge they hold. In this view, a rigid model like TRANSIT hinders innovation and alternative thinking, which in the long run may slow the development of improved methods.

In this context, Borg et al. (2014) argue that the strengths of Bayesian networks may be better utilised if a flexibility model is used. This way, the Bayesian network model could be adjusted to the uniqueness of a given project, which in turn would give a more relevant analysis and allow the model to adapt to the newest development in the field.

The dilemma between relevance and rigidity is also relevant in fire safety engineering, because buildings potentially are even more diverse than road tunnels — both with regards to building usage (living, working, manufacturing, storage, etc.)

and building layout (number of floors, influence from surroundings, number of exits, etc.). The more diverse systems under investigation mean that a rigid model would have limited applications.

However, theoretically, designers and authorities in the building fire safety industry could benefit from a rigid model similar to TRANSIT as it would be easier to compare the risk level in different buildings. Also, there would be a quicker and more consistent method to compare the impact on the risk level from different risk reducing measures. For example, a central modification factor similar to the accident modification factor (AMF) in TRANSIT could be used to compare different designs as the factor is calculated similarly for each case in a rigid model. Such a factor could be used to model the chances of successful escape in order to give an assessment of the conditions in the building investigated compared to a "standard" building, or a factor describing the probability of fire occurrence compared to a "standard" building — thus, an alternative concept of the ASET/RSET method somewhat similar to the method presented by Hanea and Ale (2009). Having such factors could give a coarse picture of the risk in the studied building compared to a standard building, which could simplify the design and approval phases.

However, the concept of a central factor is not limited to a rigid model. A flexible model could use such a factor, but it would differ from the rigid model as the variables used to calculate the factor could vary depending on the choices of the analyst. This would make comparison between different designs more tedious as the validity and comparability of the models would have to be assessed in each case. Still, the nature of a dimensionless factor would allow comparison to a certain degree and the flexibility would remove the downsides of the rigidity.

4.1.3 Uncertainty in TRANSIT

As mentioned, TRANSIT does not consider uncertainties as part of the risk picture. The only place in the TRANSIT manual, where the uncertainty of a parameter is explicitly described, is where the uncertainties regarding the probability distribution of the AMF-variable is showed — cf. figure 3.3 on page 25.

Uncertainty is important as the range of potential consequences in road tunnel accidents are broader than the range on open roads (Nævestad and Meyer, 2014) and, therefore, Borg et al. (2014) states that the expected value is of limited use for decision makers. Uncertainties could to some extend be expressed as probability distributions or simple standard deviations, but more fundamental uncertainties regarding the parameters and the model must also be communicated in order to give a thorough and fulfilling description.

Additionally, specific events that are unique to a project cannot be dealt with in TRANSIT, which introduces some uncertainty as the risk contributions from such incidents are not considered. Also, the use of expert opinions in the TRANSIT model introduces uncertainty due to the subjectivity of such statements, which is not described in the manual. Furthermore, the probability tables in the model may or may not be appropriate for the current analysis, and this is a contributor to the underlying uncertainties in the model as there is no way for the user to analyse this through sensitivity analyses etc. (Borg et al., 2014).

The lack of focus on the uncertainties is a weakness of the model. This conclusion is independent on whether a Frequentist or Bayesian perspective on risk is adopted, but the two schools differ with regard to why. Frequentists may claim that uncertainty must be described in order to understand how well the model calculates the "true" risk, whereas Bayesians may claim that uncertainty must be described in order to understand the knowledge base of the developers and thereby the validity of the model.

Seen from the Bayesian perspective on risk presented by Aven (2010) and explained in section 1.3, it is also a problem with TRANSIT that the analyst does not need to consider background knowledge, possible accident scenarios and sensitivity of parameters in order to conduct a calculation. Of course, the background knowledge is described to some extent in the documentation of the model, however, the analyst is not forced to relate to it. Thereby, the model as such does not incorporate this factor. The background knowledge on the input values is also not necessarily considered by users. Additionally, it can be hard for an analyst to identify the relevant variables for sensitivity analysis due to the vast amount of interconnections between the parameters. Generally, these issues relate to the critique presented by Borg et al. (2014) as an automated use of TRANSIT can lead to analysts negating both the influence of uncertainty, events unique to the problem at hand and the importance of sensitivity analysis.

Another aspect of the absence of uncertainty analysis in TRANSIT is the lack of knowledge about the ratio between high-probability/low-consequence events and low-probability/high-consequence events. This aspect is important as decision makers may want to reduce the probability of high consequence events even though the overall expected loss seems acceptable.

To summarise, incorporation of uncertainty and sensitivity analyses in a model is important in order to provide the necessary information for decision makers. Therefore, fire safety engineers should make an effort to include these aspects in a Bayesian network model for fire risk assessment.

4.1.4 Output

As already discussed, TRANSIT has a Frequentist or expected value approach to risk and this is also seen in the outputs from the model. Average outputs may be useful for some stakeholders, but for example the emergency services may find it difficult to decide, whether they should prepare for few high-consequence events or many low-consequence events. Therefore, Borg et al. (2014) state that the output values may be used to compare different design options, however, further analyses are needed in order to cover all aspects of the risk picture in a road tunnel. As such, TRANSIT cannot be a standalone tool and must be used together with other risk assessment techniques.

In addition to the average values, TRANSIT produces graphs that show the risk level in each tunnel segment. These graphs can be used to identify, what segments need more analysis and, offhand, where risk reducing measures would have the largest impact. However, the graphs are based on average values and do not present the uncertainty of the results, therefore, they are of limited use for the overall presentation of the risk picture.

TRANSIT does not provide information on the cost of potential accidents, fires etc. in terms of repairs and lost income due to maintenance. Such information would be relevant for tunnel owners and, in a broader perspective, key infrastructure like tunnels could influence the socio-economics of the local society. This supports the conclusion that further analyses are needed besides a TRANSIT calculation.

4.2 TRANSIT in Rogfast

As described in the previous chapter, Rogfast will be a complex and state of the art tunnel. Therefore, it is relevant to evaluate the performance of TRANSIT in such a case in order to take practical considerations into account, thereby supplementing the general evaluation given above. As mentioned, TRANSIT has only been used in one of the risk analyses of Rogfast. Therefore, both the actual use and the theoretical potential for using TRANSIT will be evaluated.

A general problem when assessing risk in state of the art projects is that historical data and knowledge has limited value. TRANSIT can to a certain extent oblige this critique as it qua its Bayesian networks structure better can cope with interconnecting parameters compared to for example fault and event trees. However, statistics and expert opinions are generally more uncertain in novel projects (Borg et al., 2014), and the conditional probability tables in TRANSIT are still based on knowledge and experience, which are not necessarily representative for Rogfast — e.g. statistical valid data does not exist for Rogfast's long segments with high gradients, thus, assumptions must be made concerning the effect on the AMF, the fire modification factor etc. Such assumptions may not be foreseen by the model, meaning that the model may not apply in practice.

Borg et al. (2014) have made a comparison between the results of TRANSIT and TUSI for the Rogfast tunnel. They found that the results from both models with regards to accidents were close, however, the TRANSIT results related to fires were only around 4 % of the results from TUSI. It cannot be concluded, which model is more correct, however, the results show that large uncertainties exist. Thus, using TRANSIT in complex and state of the art projects should be supplemented by studies in uncertainty and sensitivity, as the outputs in themselves do not give sufficient information for decisions.

4.2.1 Insufficiencies of TRANSIT

Moreover, a couple of insufficiencies appear when comparing the perspectives in the TRANSIT model and the results of the risk analyses of Rogfast.

First of all, TRANSIT does not consider the response of emergency services as none of the input parameters are related to this aspect. Response times and on-site facilities for the emergency services are not considered, and in the Rogfast project, especially response times could be a major issue due to the length of the tunnel and the concentration of response assets south of the tunnel as described by the contingency analysis (Hofseth, 2012). Also, the contingency analysis expects rescue vehicles to enter the tunnel in order to evacuate persons, however, leaving emergency response out of the model would mean that the results of the model are unaffected by rescue operations. Theoretically, the output from the model concerning fatalities would be too high as emergency services sure will save some lives in some cases — if not, their existence would be unjustified.

Thus, leaving emergency response out of the model indicate that the expected number of injuries and fatalities are assumed independent of mitigating actions — except the type of fire ventilation system in the tunnel. This leads to the next insufficiency of the model; TRANSIT cannot deal with fixed fire suppression systems. Fixed fire suppression systems are not required in Norwegian tunnels constructed using the prescriptive regulations (NPRA, 2010) and, globally, they are not often used — except from in Japan (Haggkvist, 2011). Nevertheless, they are a type of safety system that may be relevant in some tunnels. Hokstad et al. (2012) studied the effects of installing a fire suppression system in Rogfast. Although they, based on a cost-benefit analysis, ended up not recommending installing such a system, this conclusion could not have been made using TRANSIT, as the model simply do not include an analysis of this aspect.

Also, it is not possible to analyse intersecting tunnels in TRANSIT. Of course, the actual intersection can be included, but the overall assessment of a tunnel arm like the one from the main tunnel to Kvitsøy in the Rogfast project is not possible. This is a problem as the model does not take into account the interdependencies several tunnels might have and, instead, a separate analysis must be made for each tunnel. Thereby, using TRANSIT in the Rogfast project may result in leaving important parameters out of the analysis, which leads back to the critique stated above; that TRANSIT cannot deal with systems that differ from the norm.

The insufficiencies show that TRANSIT must be part of a larger analysis. Also, it would be a huge model if all parameters should be included and this could lead to a less transparent and confusing model. Therefore, it can be discussed whether a holistic model ever will be fulfilling in itself.

In relation to building fire safety, it would be natural to take emergency response into account to some extent as this parameter influences the fire safety level — cf. table 1.1 on page 5. As stated above, it does not make much sense to consider only self-rescue as an option, because emergency service operations influence the final number of injuries and fatalities — this point is no less true in relation to building fire safety, where fast and correct medical treatment is important in order to negate the effects of for example cyanide poisoning from smoke inhalation (Eckstein and Maniscalco, 2006).

Additionally, fixed fire fighting systems are much more common in buildings than in road tunnels — e.g. following the Danish prescriptive rules, automatic sprinkler systems are required in larger rooms for industrial use, large parking garages as well as care homes, hospitals and prisons of a certain size. Therefore, it would be natural to include such systems in a new fire risk model.

4.3 Preliminary Conclusions

The evaluation of TRANSIT shows that the model may be useful as a supplement to traditional risk analyses and as a tool for comparing the risk level in different tunnels. TRANSIT satisfy most of the performance goals set up by the developers, however, the model has some issues especially with regards to describing the uncertainties of the model. This aspect could be improved by better describing the background knowledge, the sub-models and the inherent assumptions.

It can be difficult to assess which parameters that have a key impact on the results due to the interdependencies of the parameters in the model, and because the model cannot describe uncertainties of neither the input nor the output parameters. Therefore, analysts might have difficulties conducting thorough sensitivity analyses. Additionally, the model outputs are in expected values and frequencies, thus, TRANSIT does not describe all aspects of the risk picture — especially if a Bayesian perspective on risk is adopted. Therefore, not all relevant stakeholders may find use of the results; e.g. the lack of knowledge about the ratio between high-consequence and low-consequence events might prove the model of little use to emergency services.

The TRANSIT model is rigid and it tries to cover all road tunnel safety aspects in a holistic way. However, this study find that not all parameters are taken into account, and the holistic approach does not help analysts that want to identify new accident modes or incorporate new knowledge not described by the model originally. Also, the rigidity of the model makes it difficult to apply it to complex tunnels that do not fit into a given standard design. In such cases, the results in themselves are of little use due to large uncertainties. As an alternative, a flexible Bayesian network model could be applied in order to better describe the uniqueness of the project.

The following chapter will apply the experiences from TRANSIT to Bayesian network models for use in fire safety engineering.

Chapter 5

Framework for Application of Bayesian Networks

In this chapter, a framework for Bayesian networks in fire safety engineering will be established. The basis of the framework is the knowledge about Bayesian networks from chapter 2 and the description and evaluation of TRANSIT in chapters 3 and 4, respectively. Additionally, the framework builds on more general observations from practice in fire safety engineering in Denmark.

It was seen in chapter 2 that Bayesian network models can have different levels of applications, for instance Bayesian networks may be used to model a single part of the overall fire process like fire spread between compartments. However, the basic assumption for this framework is that a new Bayesian network model, like TRANSIT, would have a holistic approach — understood as a focus on both risk of fire occurrence and risk of unwanted effects in case of fire. In spite of this, many of the points presented are equally valid for less holistic models.

Four overall categories have been identified as central for a fulfilling description of the framework: (i) Categorisation and limitation, (ii) key variables, (iii) modelling method and (iv) methods for handling of uncertainties. Of course, the latter category is something that should be included in all types of analyses. However, the evaluation of TRANSIT showed that in practice, developers might neglect or de-prioritise this aspect. Moreover, the international FORUM of Fire Research Directors (Croce et al., 2008) emphasise the importance of both understanding and incorporating uncertainty in fire risk analyses. As a result, the topic is directly addressed here in order to accentuate its importance and make sure developers consider it during development of a model.

The four overall categories will form the overall structure of this chapter. The framework is summarised as a number of recommendations in table 5.2 on page 56.

Table 5.1: Example of a categorisation in 36 categories based on the Danish usage categories (DECA, 2010) and fire safety guidelines (Danish Energy Agency, 2012; The 4-City Coorperation, 2013). The height "h" is the height from ground level to the top of the floor deck on the top floor.

		Usage category					
	Height h [m]	**1**	**2**	**3**	**4**	**5**	**6**
A	Single storey	1A	2A	3A	4A	5A	6A
B	]0;5.1]	1B	2B	3B	4B	5B	6B
C	]5.1;9.6]	1C	2C	3C	4C	5C	6C
D	]9.6;12]	1D	2D	3D	4D	5D	6D
E	]12;22]	1E	2E	3E	4E	5E	6E
F	]22;100]	1F	2F	3F	4F	5F	6F

5.1 Categorisation and Limitation

One of the first steps of building new models is to define what the purpose and aim of the model should be. A Bayesian network model for building fire safety would have to include several variables in order to describe the vast diversity of buildings. However, a model that adequately covers all possible types of buildings and building usage may be too detailed to apply in practice. Additionally, a model covering all buildings would require data for rare combinations of usages such as industry and accommodation in the same building. Therefore, the model should be limited according to the needs of the different stakeholders.

5.1.1 Categorisation of Buildings

One way to limit the scope of a model, while still covering the all different types of buildings, is to develop different models for the different buildings. Each model could cover a given category of buildings based on the characteristics of the building and its usage.

An obvious categorisation is based on the existing usage categories described in different national standards and regulations as done in for example Denmark (DECA, 2010) and the UK (BS 9999, 2008). Alternatively, the group of buildings could be defined based on the categories used by the emergency services as this would allow easy application of data for example as seen in the statistics from the Danish emergency services (DEMA, 2013). Either way, categorisation of buildings into different groups would mean that each model covers a more homogeneous group of buildings resulting in more efficient use of resources when building the model. Also, potentially, the more specific[1] a model is the less the inherent uncertainties are as data will be more concentrated on relevant scenarios.

An example of a categorisation based on the usage categories defined in the Danish regulations (DECA, 2010) and the demands to structural fire resistance based on height above ground level from the Danish Energy Agency (2012) and The 4-City Coorperation (2013) is seen in table 5.1.

[1] In this context, "specific" and "rigour" should not be confused; specific refers to the aim and application of the model, whereas rigour refers to the structure and user interface of the model.

It is seen that a total of 36 sub-models are needed if this principle is used — and perhaps even more as category F can be further spilt up according to the guideline (The 4-City Coorperation, 2013). However, all of the categories may not be realistic and, therefore, may not be needed in practice. Also, the workload for developing all these models does not necessarily correspond to 36 individual models as some variables and assumptions may be reused.

Still, the limits of this categorisation is that buildings with varying heights are difficult to include. Also, several usage categories typically exist within a building, therefore, this categorisation may be too coarse or rigid to be fruitful. As a result, further research in this aspect of categorising buildings in practice is needed.

5.1.2 Level of Detail

Another issue with regard to establishing the boundaries and scope of a model is to define what to include in the model and what the level of detail should be. In that context, an important point of Hanea and Ale (2009) is that the level of detail should be agreed upon by all stakeholders in order to construct a model that are seen as valid by all.

Some of the existing fire safety-related Bayesian network models described in chapter 2 are limited to or focused on sub-processes in the overall fire development such as fire spread and evacuation. These models were found to have a rather high degree of detail.

However, as mentioned, this framework intends a more holistic approach. Holistic approaches were seen in the models by both Holický (2010) and De Sanctis et al. (2011), but the models were found to be rather coarse compared to the other models. For example, the holistic models were very coarse with respect to modelling fire occurrence — especially if compared to TRANSIT.

Generally, models with a high degree of detail are most beneficial late in the design process as specific details of the design must be known. In a late phase, detailed models can provide thorough information and deep understanding of the design, which is needed for the final verification of the design. Also, detailed models potentially decrease the uncertainty as the background knowledge has to be extensive. But as a result, detailed models are of limited value early in a design phase as the required information is unavailable — see e.g. the critique of TRANSIT by Borg et al. (2014).

On the contrary, models with a low degree of detail are best used early in the design phase in order to get a preliminary analysis of different design options. However, the uncertainty of such models are larger and, therefore, they are of limited value, when analyses of the final design are to be carried out.

In TRANSIT, this dilemma is dealt with by replacing the lack of information by prior probability tables. This approach was criticised by Borg et al. (2014) as it included several inherent assumptions that may or may not be appropriate in the given case. One solution could be to develop several models. Alternatively, development of a model that can be adapted to the current needs could be beneficial.

Thus, designers could apply a coarse model at an early stage and then re-model and refine the different overall parameters to increase the level of detail as information becomes available later in the design phase. This approach is similar to the concept applied in the model presented by De Sanctis et al. (2011). Such an approach requires update concurrently with the design phase to make sure the information in the model are kept updated and reasonably detailed at all times.

5.1.3 Context

The evaluation of TRANSIT showed that one model hardly can cover all aspects of the risk picture — especially if it is generic and not system-specific. Therefore, it was concluded that the use of more general models should be applied as part of a classical risk assessment that covers the more indefinable aspects of system safety.

This point also applies to fire risk analysis as there most likely is some aspect of any project that will not be covered adequately by a Bayesian network. Thus, models should still be considered part of a process that includes hazard identification, scenario analysis and overall assessment of the risk picture as done in traditional risk assessments.

5.1.4 Applicability

The evaluation of TRANSIT showed that the use of standard models on non-standard systems may be problematic in some respects. Therefore, developing a model that covers very complex building fire safety systems as well as more standard systems may not be easily done — and it could be questioned whether it should be done at all. Despite this, developers of new models would surely like them to be applied to as many different types of buildings as possible — including non-standard or complex buildings.

In the literature, the term "complex system" is used in many different contexts including risk and safety management; however, the definition of the term is rather indistinct. For example, some define a complex system as a system with at least two interconnected subsystems (Borgonovo and Smith, 2011; Melchers, 2013), whereas others define a complex system as a system with a non-linear response (Vatn, 2011). Both of these definitions seem rather meaningless in relation to building fire safety systems as most such systems would be categorised as complex and because the physical processes in a fire are considered complex in themselves (Yung, 2008). Therefore, with no clear definition of complexity, it is left to the risk analyst to assess, whether a model is applicable in a given case.

Generally, Bayesian networks might be the best method currently available for handling complex systems due to the possibilities in modelling interconnected variables (Holický, 2010). Thus, the aim for developers is to make a model that both covers the more or less standard buildings and still can be applied to buildings with some unique characteristics.

The first group of buildings is important to cover as the model should be applicable to as many projects as possible in order to be successful and meaningful. The latter is important as thorough fire risk assessments are mostly necessary for large complex buildings or new types of buildings — at least according to the current Danish guidelines (DBHA, 2004a). The evaluation of TRANSIT showed that the key to make a model that is applicable to complex systems is flexibility as a flexible model can be fitted to a given unique problem better than a rigid and general model.

To conclude, a new Bayesian network model for fire risk assessment should clearly state that it is up to the risk analyst to assess the validity of the model in each specific case. Furthermore, steps should be taken to force users to assess the applicability and think beyond the model in general. Thereby, the concerns of Borg et al. (2014) is obliged with respect to the danger of an automated use of a model (in their case the TRANSIT model).

5.2 Key Variables

Having dealt with the general considerations on how to apply the model, what to include in the model can be discussed. Hanea and Ale (2009) state that at least four overall parameters must be included in a fire risk model: (i) The fire, (ii) the systems and environment, (iii) the occupants and (iv) the rescue services. It is noted that these variables cover the parameters described by CAENZ (Spearpoint, 2008) and seen in table 1.1 on page 5. Although Hanea and Ale (2009) do not consider the probability of fire occurrence in their model, it is easily incorporated by adding on the relevant variables.

The main parameters require several variables to thoroughly describe them and these variables have to be identified. Generally, such an identification process could be based on a combination of standards, regulations, published research and opinions of key stakeholders and experts as done in for example the development of TRANSIT (Schubert et al., 2012a).

The following sections will go into a little more detail about the data and variables needed for the different overall parameters.

5.2.1 The Fire

The fire parameter has two aspects: (i) Fire occurrence and (ii) fire characteristic and development. Both these aspects should be included in the model in order to thoroughly describe the risk picture.

The fire characteristics and fire development are fairly well-described in the literature. These variables all relate to the fuel properties such as smoke potential, calorific values, fire load, fire spread and fire growth rate — see e.g. the CAENZ design guide (Spearpoint, 2008) or the Swedish fire safety guide (Bengtson et al., 2005). Interactions between the fire and the surroundings is also important as it relates to fire and smoke spread, activation of fire safety installations and other such parameters.

On the other hand, fire occurrence is a less studied subject. However, it is known that modelling fire occurrence in detail requires several variables. According to the CAENZ fire engineering guide (Spearpoint, 2008), fires are in general started as a result of piloted ignition, spontaneous ignition or spontaneous combustion in bulk fuels. Therefore, causes for these three types of ignition should be included.

The probability of fire occurrence has been studied based on statistical data by both Lin (2005) and Rahikainen and Keski-Rahkonen (2004). Both studies found that the likelihood of a fire occurring is highly dependent on the type of occupancy. Additionally, Rahikainen and Keski-Rahkonen (2004) found that fire occurrences differ as a function of the time of day, day of week, week of year and month of year. They also found that there is a correlation between the total floor area of a building and the probability of fire occurrence per floor area.

All the mentioned variables should be incorporated in a model to a reasonable extent and it should be studied how they influence each other — for example, the ignition sources in a building might change during the seasons. Additionally, further possible variables should be identified. Of course, the considered number of variables depends on the desired degree of detail of the model.

Developers can be inspired by for example Cheng and Hadjisophocleous (2011) and Matellini et al. (2013) for how to construct the part of the Bayesian network regarding the fire characteristics and development. Figure 5.2 on page 50 shows an example of how probability of fire occurrence could be modelled, however, the framework must be further developed to understand all the aspects of the figure.

5.2.2 Systems and Environment

The second type of variables considered are the ones relating to the systems and environment. Here, the environment is understood as all the different geometric and physical factors and effects that influence the fire situation. This includes variables such as building geometry, adjacent buildings, weather conditions and the number of escape routes and their dimensions. The different active and passive fire safety systems are also included here — see e.g. the CAENZ design guide (Spearpoint, 2008) for a list of possible variables to include.

Common for these variables is that they are tightly linked to the choice of design. Therefore, the variables in this category should include the actual known conditions in or around the building. This imply that the variables has a low degree of uncertainty, however, uncertainties still exist due to the less certain effects of the known variables on the fire or occupant behaviour.

Examples of detailed modelling of the surrounding environment and its effects on fire development and egress conditions can be seen in the models by both Cheng and Hadjisophocleous (2011), Hanea and Ale (2009) and Matellini et al. (2013).

5.2.3 Occupants

The third type of variables concerns the occupants. They relate to the number and density of occupants, knowledge of the building and the emergency exits and their emergency training. It also includes the physical and psychological state of the occupants such as walking speed, their level of awareness and their willingness to evacuate the building. A full description of the parameters and considerations regarding occupant behaviour in building fires can be found in the NFPA Fire Protection Handbook (Cote, 2008).

The variables concerning occupant behaviour depend on the fire safety installations, the type of occupancy etc. Bayesian network modelling of occupant behaviour in dwellings has been done by Matellini et al. (2013), which may serve as inspiration for new models.

5.2.4 Emergency Service

The fourth and final set of variables relate to the effects of the emergency service on the processes. According to Hanea and Ale (2009), the response and actions of emergency services should be included in the model in order to study their influence on the fire and evacuation processes. The effects of the emergency services can include both delay of evacuation due to cross flow between occupants and fire fighters, rescue of trapped occupants and actual fire fighting activities.

The importance of including this aspect was discussed in relation to the evaluation of TRANSIT. Here, it was concluded that also the correct medical treatment was important. Therefore, not only the intervention of the emergency service have an influence, but also to some extent the pre-hospital treatment and the distance to hospitals.

According to Yung (2008), the time for emergency services to commence rescue and fire fighting operations depends on three main factors, namely notification time, response time (consisting of dispatch time, preparation time and travel time) and set up time. Of course, these variables depends on further variables, but again, the level of detail of the model determine how much to include in the model.

Of the Bayesian network models studied in chapter 2, Matellini et al. (2013) presents the most detailed model for emergency service intervention. A different type of risk-based model concerned with emergency service intervention is the model presented by Hansen (2012). Her model builds on a relative risk perspective to model the risk in high-rise residential buildings. In that model, the sub-model for calculating intervention time builds on data and experiments in Denmark and abroad in order to model both the time for the emergency service to arrive on scene and the time for reaching the location of the fire.

An example of a Bayesian network for calculation of intervention time is seen in figure 5.1. In the example, the type of emergency service (ES) refers to the preparation time as part-time fire fighters generally requires more time to leave the fire station compared to full-time fire fighters. The efficiency of the emergency service (ES) refers to the training of fire fighters, which influence the set up time as well as the time to leave the station. The example could be extended for instance by making a more detailed model for the set up time and notification time. Such extensions could include the awareness of occupants and the building geometry, which further could be a function of type of occupancy etc. Also the other variables could be further developed (or simplified) based on the desired level of detail of the model.

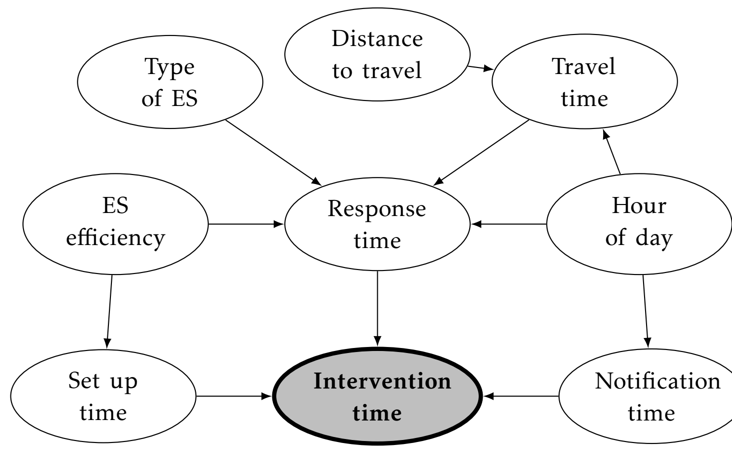


Figure 5.1: An example of a Bayesian network model for calculation of the intervention time of the emergency service (ES).

5.3 Modelling Method

After a decision on how to limit the scope of the model as described in section 5.1 has been made and after the relevant variables have been identified, it must be determined how to construct the actual model. This section discusses different aspects of that challenge.

5.3.1 Data Collection

Developers should include many different sources in the collection of data — both when it comes to identifying variables as discussed in the previous section, but also when it comes to modelling these variables. Of course, historical data must be used to its full potential, however, Bjelland (2013) states that also less obvious data must be incorporated in safety analyses. The reason is that unique combinations of systems and new failure modes do not appear in historical data. Also, the data sets on rare combinations is typically too scarce to be applied validly without some degree of processing by the analyst (Aven and Heide, 2009).

In TRANSIT, the cases with scarce historical data were dealt with by incorporating expert judgements (Schubert et al., 2012a). Expert judgements can be obtained by different procedures such as committees and panels — see e.g. Donegan (2002).

One procedure is the Delphi technique — a method for organising meetings with different experts. Whether the Delphi technique is applicable to fire safety engineering has been discussed in the past. Shields et al. (1987) claim that the technique has methodological problems as subjectivity is introduced in the assessments and because experts can influence and convince each other in some versions of the technique. Thereby, the experts may indulge to group thinking that can lead to them overlooking crucial points, Shields et al. argue. Additionally, Shields et al. claim that the process of selecting appropriate experts can be problematic as "experts" or "specialists" are not well-defined terms.

Despite the argument over its applicability, the Delphi technique has been used in fire safety engineering in different contexts. The use include development of a trading logic for fire safety measures (Harmathy et al., 1989), fire risk assessment of high-rise timber constructions (Karlson and Larson, 2000) and assessment of fire safety management practices (Baker et al., 2013). On this basis, the use of expert judgements could be valid, however, they should be applied with caution.

The evaluation of TRANSIT showed that using data from foreign countries can be problematic, if the reasoning is not explained. Therefore, developers of new models must use data with consideration to the special factors that may apply in different countries.

To summarise, the use of expert opinions is inevitable due to lack of statistical data and due to the many interconnected phenomena in fires and safety systems. However, the arguments above show that the collection of expert opinions should be conducted by well-considered and thought out manner. Additionally, data from foreign countries should be applied with thought as different factors may be involved.

5.3.2 Segmentation

The discussion about categorisation of buildings and limiting a model showed that differences inside a building may prove it difficult to make overall categorisations based on for example usage categories. However, this could be easier if only part of the building was studied. Thus, a model for fire risk analysis could benefit from the idea of different segments with a constant risk profile as seen in TRANSIT.

In buildings, an obvious choice for a segment would be a room, but a fire section or an entire floor could also be a segment depending on the situation, the input data and the level of detail. For example, insurance companies could benefit from a model describing fire sections as the insurance premium typically is based on the potential property loss. On the other hand, models concerned with occupant safety might have another need for segmentation.

The advantage of segmentation is that averages of differences within a building would be avoided and, instead, the uniqueness of each segment could be modelled. However, high risks or uncertainties in some segments could be overlooked if only the results for the entire building are regarded. Therefore, a model using this approach should clearly communicate the results for each segment as done in TRANSIT.

5.3.3 Centralisation of Variables

As seen in section 5.2, a detailed Bayesian network model could include a long list of variables. The evaluation of TRANSIT showed that models for fire risk assessment could benefit from combining different variables in a central factor similar to the accident modification factor (AMF). This would make it easier to consistently model the different parameters and would require less tedious comparison between different variables.

As mentioned, the AMF is developed to assist in modelling occurrence of an accident. Therefore, it would be obvious to develop a similar factor to combine the variables concerning fire occurrence — a Fire Modification Factor (FMF). An example of this is seen in figure 5.2, where some of the variables concerning probability of fire occurrence described in section 5.2.1 are combined.

Centralisation requires knowledge about how the different variables individually influence the FMF in order for the method to work. Also, a standard must be described somehow in order to relate the different variables. Therefore, this approach requires further study and can not be directly applied.

Despite that the example applies to the FMF, a modification factor could also be used to model other phenomena as a reference to a standard value or an acceptance criteria. Examples of this were discussed in the evaluation of TRANSIT.

5.3.4 Degree of Flexibility

Basically, a holistic model could be made by two different approaches: A rigid model or a flexible model. A fully rigid model would, like TRANSIT, be locked to the user. On the other hand, a fully flexible model would not so much be a model in classical terms, but it would be a set of data and a guideline for how to construct a specific Bayesian network for a specific project. Or in other words, a fully flexible model would have to be built from scratch for each individual project. Of course, it is also possible to do something in between. This could be a set of rigid sub-models that could be combined in each given case to model individual projects.

As discussed in the evaluation of TRANSIT, rigid models can be challenging to apply in practice — especially in complex and state of the art projects. This suggests that more flexible models, where users can customise the model to the problem at hand, are favourable. This way, the analyst will get the best possible fit of the model to the problem at hand and the assumptions in the model will be most fitting.

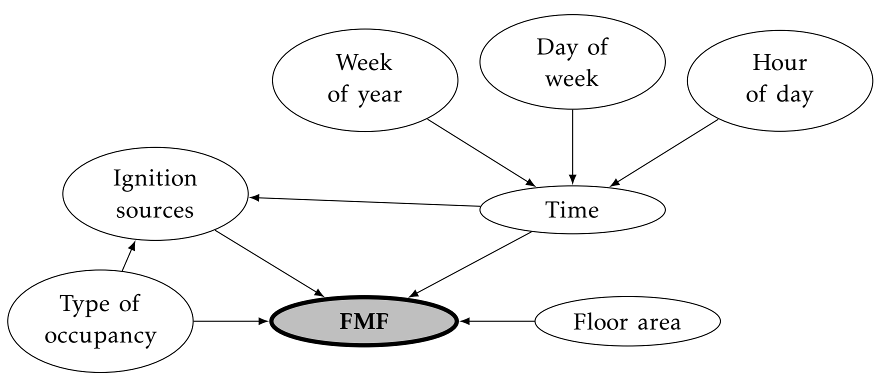


Figure 5.2: An example of how to combine relevant variables in a central Fire Modification Factor (FMF).

Moreover, during the evaluation of TRANSIT, it was argued that highly rigid models would hinder innovation and development. This further suggests that flexible models are used.

However, a highly flexible model requires a higher amount of work each time it is applied to a new building. Therefore, it might be beneficial to have different degrees of flexibility based on the different types of buildings — standard type dwellings may be more alike than state of the art public and commercial buildings. Thus, the degree of flexibility depends on the actual use of the model.

5.4 Handling of Uncertainties

The evaluation of TRANSIT showed that communication of uncertainty and sensitivity of variables is important, if the results are to be useful for most stakeholders. In order to better understand the concept of uncertainty, a conceptual dispute will be outlined, before the proposed way of dealing with uncertainty is presented.

On one side, it is argued that distinction between aleatory[2] and epistemic[3] uncertainty is important as there is a clear difference between the two (Parry, 1996). According to Parry (1996), separation of the two types of uncertainty lets analysts express both the uncertainties in the world and the uncertainties of the analysts and the model due to insufficient knowledge. Thereby, decision makers are presented with an overview over the uncertainties that can be improved, if more resources are put into the risk analysis, which is a strong advantage (Der Kiureghian and Ditlevsen, 2009).

On the other side, Winkler (1996) argues that probability is the same concept regardless of the source. Distinction between types of uncertainty may be beneficial in some cases but, fundamentally, probability is a measure of degree of belief. Thereby, Winkler (1996) assume a Bayesian approach in which all uncertainties fundamentally are epistemic as there is a true (but unknown) state of the world (Nilsen and Aven, 2003). Further, Winkler (1996) states that analysts should cut straight to the core of the matter and minimise the uncertainties instead of spending resources on categorising them.

Although, the categorisation of uncertainties may be beneficial in some cases, it can be argued what is gained by introducing a distinction in a large model as a fire safety model inevitably will be. Instead, it should be left to the analyst to assess each of the associated uncertainties — the knowledge about a given variable should be improved, if it is found to be inadequate for the purpose no matter the type of uncertainty.

[2] Aleatory uncertainty is the uncertainty of a parameter due to statistical fluctuations or inherent natural variability (Faber, 2012).

[3] Epistemic uncertainty is the uncertainty occurring from lack of knowledge of a phenomenon or parameter (Faber, 2012).

5.4.1 Communication

In general, the sources of uncertainty in models originates from the input data and the inherent assumptions of the model. During the evaluation of TRANSIT, it was found that communicating uncertainties is an important aspect of a model, if the results are to be used by the broad majority of stakeholders.

The expert opinions that will be needed to build a model for complex fire safety systems is one source of uncertainty. Therefore, these statements must be thoroughly described in the documentation in order for the user to understand both how to treat the results and what the limitations of the model are. Thus, the uncertainty of the assumptions can be treated by providing good and transparent documentation. This does not mean that the uncertainties are limited, but it provides the required insight to the analyst to apply the model in a valid manner.

Furthermore, the outputs of a model should to some extent communicate the uncertainties. This is important in order to avoid outputs that are single numbers as seen in TRANSIT. Single values might lead users to ignore the variations in fire phenomena — thus, single value results could lead to the same critique as presented by Babrauskas et al. (2010) with respect to the ASET/RSET method.

5.4.2 User Access to Assumptions

As mentioned in the evaluation of TRANSIT, uncertainty of the assumptions in the model can be reduced by letting the user be able to alter them. That way, users can fit the model to the given subject of analysis and they can discard the unfitting assumptions. For this to work, the model must be constructed with some degree of flexibility.

A method for dealing with uncertainty and contradiction of expert opinions related to fire safety systems is presented by Helton et al. (2005). This method imply that the analyst considers expert judgement and data as variables instead of fixed values. Thereby, the output of the calculation will not be a single number, but an interval, a probability distribution or similar. This method could also be applied in Bayesian networks to a certain extent as the states of the variables could be formulated as intervals.

5.4.3 Uncertainty of Input

A way to address the uncertainty of input parameters is to model some input variables as probability distributions. For example, variables could be described by both the expected mean value and the standard deviation. This method has been used by Cheng and Hadjisophocleous (2011) in their Bayesian network model, and input as distributions is seen in for example the work of Helton et al. (2005).

In general, the inputs where this approach is relevant are the ones with more or less stochastic variations. In the model by Cheng and Hadjisophocleous (2011), variables like fuel density and fire resistance rating are treated this way. Additional relevant variables include the occupant density or occupant load (as a supplement to variations due to the time of day) and the response time of the emergency service. On the other hand, the use of probability distributions in describing variables such as geometry and the presence of specific fire safety installations makes little sense as the analyst should know the states of them with high precision.

Thus, uncertainty of input can be addressed by modelling relevant parameters as probability distributions.

5.4.4 Sensitivity of Variables

Another aspect relating to describing uncertainties is the sensitivity of variables. It is widely acknowledged that sensitivity analysis is important in order to assess both the importance of each variable and the general validity of the model — this also applies to Bayesian networks. Additionally, Aven (2010) states that sensitivity is an important parameter for describing risk as mentioned in section 1.3.

Building designers would benefit from models providing outputs that were consistent and easily applicable to sensitivity analysis as it would be simple to get an overview of the robustness of the model. Thereby, sensitivity analysis could be used to analyse which type of fire safety installation is most robust to small changes in the assumptions.

In practice, sensitivity analyses of Bayesian networks can be carried out as done by Matellini et al. (2013) for their model. They use a classical sensitivity analysis of the different variables but, additionally, their model output the likelihood of all the variables as seen in figure 5.3. Such a figure gives an overview of the

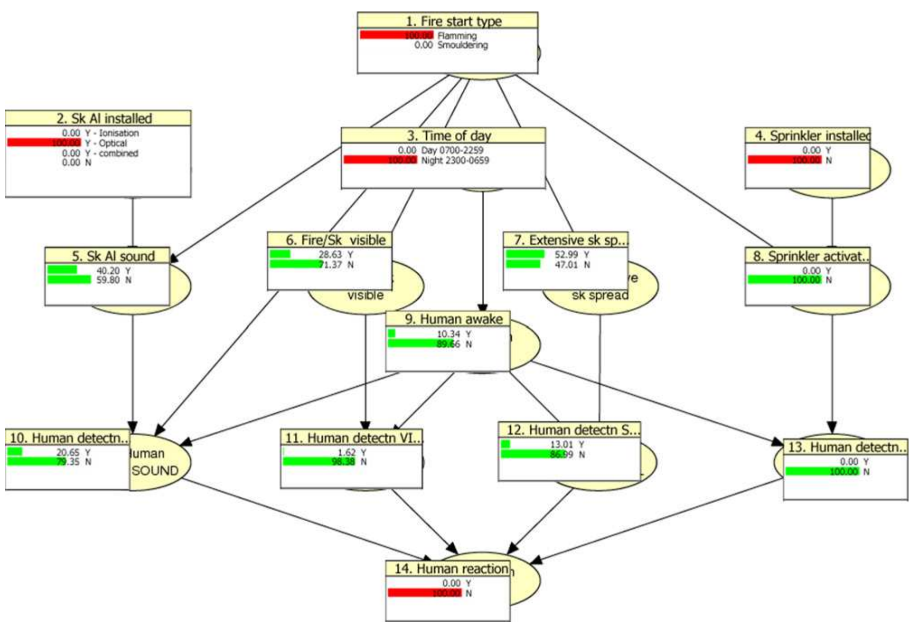


Figure 5.3: The probability of each variable in the model by Matellini et al. based on insertion of evidence in 5 variables (red) (Matellini et al., 2013).

different possibilities in the model that may be better than the one presented in for example TRANSIT — in TRANSIT only the final outcomes are described, so the user does not see the intermediate steps and how they affect the final result. Also, the overview by Matellini et al. (2013) makes it easier to conduct sensitivity analyses on both the intermediate variables as well as the final outcome, which better describe the overall picture.

5.4.5 Model Uncertainty

The final aspect of uncertainty described in this framework is the uncertainty of the model. Model uncertainty can be defined as the difference between the outcome of the model and the actual outcome in the real world. Although description of uncertainty is important, it is debatable whether model uncertainty should be dealt with explicitly. According to Nilsen and Aven (2003), focus on model uncertainty diverts the attention away from the sources of uncertainty and the crux of the matter, namely the uncertainty of the phenomenon under investigation.

According to Nilsen and Aven (2003), model uncertainty may arise from two sources: (i) Limitations to the analyst's knowledge and (ii) deliberate (and unconscious) simplifications. The latter source originates from choices made by the analyst due to limited resources, or from an assessment that the model is sufficiently accurate for the purpose of the analysis. This source of uncertainty will always be present in some form as the purpose of the model is to simplify a complex world and present selected results. However, the model should only be applied to systems, where this uncertainty can be justified (Nilsen and Aven, 2003).

Additionally, from a Bayesian perspective on risk and uncertainty, the model does not introduce new uncertainty. Instead, the model itself is used to measure the uncertainty and, thereby, the outcome of the model is the most reliable result available based on the belief of the analyst (Nilsen and Aven, 2003). Therefore, Aven (2010) states that models should be optimised and refined to an extent, where the model is the best tool to describe the risk level. Of course, if this is not the case, the model should not be used at all as other models will be better suited for the task.

Furthermore, Aven (2010) states that the entire concept of model uncertainty is rather self-contradictory. The argument is that it is not possible to measure the uncertainty of the model as the actual state of the world — the true risk — is unknown. If the true risk was known, there would be no need for the model at all. Therefore, quantification of model uncertainty seems unnecessary.

Based on these observations, it is concluded that an effort to measure the model uncertainty should not be made.

5.5 Summarising the Framework

The framework presented above includes four main categories of recommendations on how to apply Bayesian networks in fire safety engineering. The four main categories are: (i) Categorisation and limitation, (ii) key variables, (iii) modelling method and (iv) methods for handling of uncertainties.

A total of 19 specific recommendations were developed. These included both specific recommendations on which variables to consider and how to collect data as well as more conceptual considerations on the nature of uncertainty. The conclusions of each of the recommendations are summarised in table 5.2.

Even though the framework is intended as a basis for holistic models, many of the recommendations are equally applicable to Bayesian network models used for different sub-processes. Such sub-processes could be the probability of fire occurrence, the probability of failure of a fire safety system or the probability of fire spread from compartments. Thereby, potential lack of data for detailed holistic models is no hindrance for the use of Bayesian networks in the study of phenomena with a more solid scientific knowledge.

The framework presents only few specific answers to how an actual model should be developed. However, it can be used as a guide for developers to deal with the conceptual design problems that may occur during construction of a model. Thus, the framework allows developers of new models to focus on the actual work like data collection and modelling of causal relations between variables. Additionally, the framework may serve as inspiration for developers of risk-based models as the potential of Bayesian network models is explained. Thereby, this framework is a first step to develop enhanced risk-based design tools for use in fire safety engineering.

Table 5.2: Summary of the recommendations to new fire safety-related Bayesian network models with reference to the section in which the recommendations are described.

Category	**Recommendation**	**Section**
Categorisation and limitation	Develop a clear categorisation of buildings and make separate and unique models for each category.	5.1.1
	Consider the level of detail based on the needs of designers, authorities, insurers and other stakeholders.	5.1.2
	Do not let the model stand alone, but use the results as part of a more classical risk assessment.	5.1.3
	Force user to assess model applicability in each given case.	5.1.4
Key variables	Fire: Fire occurrence, fuel characteristics, smoke movement, fire spread etc.	5.2.1
	Systems and environment: Building geometry, neighbouring buildings, fire safety installations, number of exits etc.	5.2.2
	Occupants: Number, physical and psychological state, knowledge of the building, emergency training etc.	5.2.3
	Emergency service: Intervention time, capabilities, effects on fire etc.	5.2.4
Modelling method	Include both historical data and expert opinions, but also include the possibility to incorporate new failure modes.	5.3.1
	Spilt buildings into homogeneous segments in order to minimize the use of average values.	5.3.2
	Summarise interconnecting variables in a central factor in order to relate the building under investigation to a standard value/acceptance criteria and in order to normalise the different impacts of variables.	5.3.3
	Provide a highly flexible model in order to allow description of the unique characteristics of different buildings.	5.3.4
Uncertainties	Do not distinguish between different types of uncertainty as this shifts focus from the main problem.	5.4
	Clearly communicate uncertainties and sensitivities of the model and variables.	5.4.1
	Allow users to edit the assumptions in the model including probability tables.	5.4.2
	Model relevant input variables as probability distributions.	5.4.3
	Incorporate feature to conduct easy sensitivity analyses of parameters.	5.4.4
	Results of all variables should be available to the user in order to conduct sensitivity analyses.	5.4.4
	Model uncertainty should not be quantified.	5.4.5

Chapter 6

Discussion

In this chapter, the potential of risk-based design is discussed in a Danish perspective. But first, the methods used in the study are reviewed in order to assess the validity of the findings.

6.1 Assessment of Methods

The methods used in the study include the use of cases to study phenomena. Additionally, a Bayesian perspective on risk has been adopted which implies certain views on risk and safety. These topics are discussed in this section.

6.1.1 Case Study Approach

A keystone in the work has been the focus on selected models and the application of the TRANSIT model in the Rogfast project — thereby, a comparative case study method has been applied. As stated by Eisenhardt (1989), case studies may lead to overcomplicated theories as complex phenomena are studied in a context, which comprise large uncertainties. Also, case studies may lead to wrong conclusions, if too few or wrong cases are considered.

The framework presented in chapter 5 can hardly be described as detailed or complicated due to the very general terms used. However, the basis of many of the conclusions — the evaluation of TRANSIT — may be distorted by the focus on an extreme case such as Rogfast. One might have found the model more adequate in many ways, if it had been evaluated based on a more standard tunnel.

However, one of the purposes of the case was to test the potential in building a model that covers both standard and non-standard cases. Therefore, it can be argued that many of the flaws of TRANSIT would have been overlooked, if a less complex case had been chosen. Also, it has been argued that buildings are more diverse than tunnels, thus, a Bayesian network model for buildings would more often encounter atypical cases. As a result, it is more important to develop a model that can handle as diverse types of cases as possible for application in fire safety engineering. In this context, the choice of a complex case and the resulting conclusions is considered most fitting.

6.1.2 Risk Perspective

Another foundation of this work is the Bayesian perspective on risk. The perspective is seen in the analysis of TRANSIT and the development of the framework for Bayesian network models in fire safety engineering. However, from the perspective of a Frequentist, some of the points, conclusions and critique may seem misplaced or outright wrong.

Frequentists may argue that the framework presented in the previous chapter focus on the belief of the developers of new models instead of focusing on the observable state of the world. Also, Frequentists may argue that a more rigid model may be preferable, if the model describes the fixed "true" state of the world sufficiently. As response, Bayesians may say that the true state of the world will always be unknown and as a result, a flexible model that takes into account the uncertainties in each case is better suited for design purposes.

An alternative view on the feud is given by Williamson (2013) who argues that both Frequentist and Bayesian methods are needed in order to carry out probabilistic reasoning correctly. According to Williamson, Bayesians need Frequentist methods, for example to establish prior probabilities. Likewise, Frequentists need Bayesian methods for example to justify application of overall results to a single case. Thereby, it is argued that the different approaches should be applied to the different problems that are seen as best fitted for their use, instead of seeing them as opposites and conflicting. From the perspective of validity and reliability, this is also the main point of Aven and Heide (2009). They state that Bayesian methods are better suited for analysis of rare events and scenarios with limited data.

On this basis, the Bayesian approach was seen as best fitted for the purpose due to the high complexity and at times large uncertainties inherent in fire science and tunnel safety — retrospectively, the results have not altered the view on this matter.

6.2 Risk-Based Design in a Danish Perspective

With an acceptance of the methods, the future and potential of the work will be discussed. The work was motivated by a wish to enhance the methods currently used in Danish fire safety practice. Therefore, it is natural to assess the potential of the framework in this context.

A risk-based model do not necessarily replace the use of deterministic analysis tools like CFD models as such tools gives detailed knowledge of specific scenarios and conditions. But a risk-based analysis casts light on the non-extreme and not worst case events regarding a specific design, which provides a wider perspective on the design. Also, a risk-based approach better describes the probability of fire occurrence compared to current methods — cf. chapter 2. To include this aspect of risk in the assessment of building fire safety designs results in a more robust and fulfilling risk picture, which in turn leads to better decision making regarding building design.

A fundamental difference from current practices to risk-based designs is the explicit acceptance of fatalities. Currently, the Danish guideline (DBHA, 2004a) states that no occupants must experience critical conditions during a fire, if all fire safety installations are operational. Occupants might be exposed if one or several systems fail, however, this aspect is not addressed in the guideline. As a result, it is left to the local municipality to assess and allow specific designs, which may lead to regional differences despite uniform legislation due to the subjectivity of the individual authority.

From a risk perspective, fatalities have to be addressed directly as there will always be a (small) probability of a fire or occupant load that leads to exposure of occupants. Typically, these events are not taken into account due to application of the ALARP principle or similar. However, this mean that safety of occupants is not guaranteed which, in theory, is a violation of the regulations.

Therefore, a basic change of attitude towards fatalities in fires is needed in order to implement quantitative risk-based designs in Denmark; an explicit acceptance criterion is needed. Of course, this does not imply an acceptance of a net increase in the fatalities in fires, however, an acceptance criterion could help assess whether the current level is reasonable from a cost-effective perspective.

One may argue that the pre-accepted solutions can provide such a risk acceptance criterion, however, a study from Norway found that the safety level of different pre-accepted fire safety concepts vary considerably (Bjelland and Njå, 2011), and there is no indication that this is not the case in Denmark, too. Additionally, the study by Bjelland and Njå (2012) presented in chapter 1 showed that a comparison to prescriptive regulations shifts focus away from the safety margin of the design. Therefore, a public debate on the subject and an official criterion is needed before the full potential in risk-based designs — including the framework presented in this study — can be utilised.

Wolski et al. (2000) presents how a risk acceptance criterion for use with risk-based design codes can be established. They suggest that a Expected Risk to Life (ERL) level is defined and that the calculated risk levels in new designs are compared to this value. The ERL should be calibrated to meet the public perception of risk. However, Wolski et al. (2000) argues that the perception of risk depends on the type of occupancy. Therefore, the calibration of ERL should take the use of the building into account to accommodate this.

An attempt to establish a national Danish acceptance criterion based on a concept similar to ERL was made by Nystedt et al. (2002). Despite the effort, the study concluded that an acceptance criterion could not be determined. The reason was that the fire risk analysis methodology was found to be questionable as standardised input data and calculation methods lacked. Hence, the level of subjectivity of calculations was too high to be applied uniformly throughout the industry, Nystedt et al. argued. Despite this, they argue that risk-based methods can be adopted by assessing the results using engineering judgement.

But other work regarding acceptance criteria is found in the literature. Nathwani et al. (1997) present a method to evaluate the value of the life of a person. This is done through the Life Quality Index (LQI), which is based on three main components: The creation of wealth, the duration of life and the time available to enjoy life in good health (Nathwani et al., 1997). By applying the LQI, it is possible to assess whether installation of further risk-reducing measures is worth the installation cost. De Sanctis et al. (2011) have used the Life Quality Index (LQI) as an acceptance criterion for their Bayesian network model.

Thus, a risk acceptance criterion is required if the full potential of risk-based methods should be utilised. Methods to establish such a criterion exist. Despite the failure of Nystedt et al. (2002), the fire safety community must on a regular basis assess the possibilities to set up such criteria as risk-based calculation tools as well as the knowledge and data are constantly enhanced. Risk-based methods can be used by comparing new buildings to pre-accepted solutions until a widely acknowledged acceptance criteria is introduced in Danish fire safety engineering, however, designers should be aware of the flaws of this approach.

Chapter 7

Conclusion

This study had two main goals: (i) To assess the potential of using Bayesian networks in fire safety engineering and (ii) to develop a framework for how to apply Bayesian network models to assess fire risk.

The study found that Bayesian network models have been used in many different fields. Furthermore, it was found that fire risk assessments could benefit from using Bayesian networks as they describe interdependencies better than current methods. Therefore, it was concluded that there is a great potential for using Bayesian networks in fire risk analysis.

The study continued by developing a framework for use of Bayesian network models in fire safety engineering. Existing models were found in the literature and studied. It was seen that often, these models consider only parts of the overall risk picture or certain phenomena within the overall fire processes. Two models were found to consider fire risk in a more holistic approach, however, these model was found to be rather coarse and not suited for detailed analysis as needed by building designers and authorities late in the design phase.

Based on the findings, the study turned to the field of road tunnel safety in order to learn from models applied in practice. In road tunnel safety, a Bayesian network model called TRANSIT has been developed and applied based on the state of the art knowledge in this field. The model consists of two networks and considers the three main risk contributors in road tunnel safety: Traffic accidents, fires and accidents involving hazardous materials. TRANSIT was evaluated based on general observations but, additionally, the application of it in a Norwegian tunnel project called Rogfast was assessed. Upon completion, Rogfast will be the longest and deepest road tunnel in the world and the tunnel is in many ways regarded complex and state of the art. Therefore, the project was deemed fitting for testing the limitations of TRANSIT.

The evaluation of TRANSIT showed that the model has some general flaws. This is partly due to the strong focus on expected values without any notable possibility to assess uncertainty and sensitivity of the variables and outcomes. The model was found to be rigid and, thereby, it is difficult to apply to projects like Rogfast, which have several unique characteristics. Also, it was found that TRANSIT leave out key variables like emergency response and that it is not possible to include new accident modes in the model. Overall, this was found to limit the potential use of the model.

Despite the flaws, some of the concept of TRANSIT was found to be applicable to fire safety-related models. These concepts included a central factor that summarised the different variables that impact the fire risk level and the idea of splitting a system into segments with a constant risk profile.

Based on both the evaluation of TRANSIT, the existing Bayesian network models in fire safety engineering and general reflections on the matter, a framework for development of future fire safety-related Bayesian network models was presented. The framework consists of 19 recommendations split in 4 general categories. The recommendations cover the questions of how to categorise buildings in order to limit the scope of a model, which variables to include in the model, which methods to use to construct the model, and how to deal with uncertainties. It was claimed that the recommendations should be followed in order to treat fire risk adequately in a Bayesian network model. Generally, the framework emphasises the importance of assessing uncertainties of variables and results. The full list of recommendations is found in table 5.2 on page 56.

It was found that Bayesian network models can be used as a powerful tool in fire risk analysis. Furthermore, it was found that a framework that describes how to apply Bayesian networks could be established — and this was done.

7.1 Further Research

The product of this work is merely a framework or guideline for future research in the use of Bayesian networks in fire safety engineering. Therefore, a natural next step would be to develop an actual model. This implies several studies. First, a study of the types of variables needed to satisfactory describe building fires is needed. Afterwards, the mutual causal relations of the variables has to be identified, before the work with collecting the data can begin. The data are needed in order to construct the prior and conditional probability tables and should be collected based on the methods presented in the framework of the present study. When a model is developed, further work exist in testing, assessing and validating it, before it can be applied in practice and used in actual design in the building industry.

Another type of work exists in assessing and establishing new risk-based acceptance criteria. This work must be completed before a Bayesian network model (or any risk-based model) can be fully utilised. The criteria are needed in order to apply a risk-based model, if the results are to be treated consistently. Currently, the lack of explicit acceptance criteria means that Bayesian network models may only be used in comparative studies of the risk level in different buildings.

The framework presented in this work is focused on building design. However, an alternative use of Bayesian networks in fire safety engineering could be application in emergency decision support. Here, Bayesian networks could be used by emergency services or operational managers to make risk-informed decisions based on real-time inputs from the situation at hand combined with general knowledge of the phenomenon. For example, incident commanders could use such a tool to help assess whether further forces should be summoned based on the current accident scenario and experience. The tool could be applied as part of the framework presented by Körte (2003), but investigations of how Bayesian networks can be applied in such a practice have to be conducted. Such investigations could result in a framework similar to the one presented in this report, which in turn could lead to development of a model.

Bibliography

AIBN (2013). Rapport om brann i vogntog på RV 23, Oslofjordtunnelen, 23. juni 2011. Technical Report 2013/05, Accident Investigation Board Norway. (In Norwegian).

Ale, B. (2009). *Risk: An Introduction*. Routledge.

ATMB (2014). The Mont Blanc Tunnel. `www.atmb.com/atmb/en/tunnel/25/the-mont-blanc-tunnel/the-history-of-the-tunnel/the-fire-of-1999.html`. Autoroutes et Tunnel du Mont Blanc. (Accessed March 20, 2014).

Aven, T. (2010). *Misconceptions of Risk*. Wiley.

Aven, T. and Heide, B. (2009). Reliability and validity of risk analysis. *Reliability Engineering and System Safety*, 94:1862–1868.

Babrauskas, V., Fleming, J. M., and Don Russell, B. (2010). RSET/ASET, a flawed concept for fire safety assessment. *Fire and Materials*, 34:341–355.

Baker, J., Buchlaghem, D., and Emmitt, S. (2013). Categorisation of fire safety management: Results from a Delphi panel. *Fire Safety Journal*, 59:37–46.

Bengtson, S., Jönsson, R., and Frantzich, H., editors (2005). *Brandskyddshandboken*. Brandskyddslaget & Lund University. (In Swedish).

Bjelland, H. (2013). *Engineering Safety with Applications to Fire Safety Design of Buildings and Road Tunnels*. PhD thesis, University of Stavanger.

Bjelland, H. and Aven, T. (2013). Treatment of uncertainty in risk assessments in the Rogfast road tunnel project. *Safety Science*, 55:34–44.

Bjelland, H. and Njå, O. (2011). Performance-based fire safety — Risk associated with different designs. In Bérenguer, C., Grall, A., and Soares, C. G., editors, *Advances in Safety, Reliability and Risk Management*, pages 224–232. CRC Press.

Bjelland, H. and Njå, O. (2012). Interpretation of safety margin in ASET/RSET assessments in the Norwegian building industry. In *11th International Probabilistic Safety Assessment and Management Conference and the Annual European*

Safety and Reliability Conference 2012 (PSAM11 and ESREL 2012), pages 2421–2430. IAPSAM & ESRA.

Borg, A., Bjelland, H., and Njå, O. (2014). Reflections on Bayesian network models for road tunnel safety design: A case study from Norway. *Tunnelling and Underground Space Technology*, 43:300–314.

Borgonovo, E. and Smith, C. L. (2011). Study of interactions in the risk assessment of complex engineering systems: An application to space PSA. *Operations Research*, 59:1461–1476.

BS 9999 (2008). *Code of Practice for Fire Safety in the Design, Management and Use of Buildings*. British Standard — BSI Standards Publication.

Carvel, R. and Marlair, G. (2005). A history of fire incidents in tunnels. In Beard, A. and Carvel, R., editors, *Handbook of Tunnel Fire Safety*, pages 3–41. Thomas Telford.

Cheng, H. and Hadjisophocleous, G. V. (2009). The modeling of fire spread in buildings by Bayesian network. *Fire Safety Journal*, 44:901–908.

Cheng, H. and Hadjisophocleous, G. V. (2011). Dynamic modeling of fire spread in building. *Fire Safety Journal*, 46:211–224.

Cote, A. E., editor (2008). *Fire Protection Handbook*. National Fire Protection Association, 20th edition.

Croce, P. A., Grosshandler, W. L., Bukowski, R. W., and Gritzo, L. A. (2008). The International FORUM of Fire Research Directors — A position paper on performance-based design for fire code applications. *Fire Safety Journal*, 43:234–236.

Dahle, G. A., Andersen, J. H. S., and Børresen, B. A. (2006). E39 Rogfast — KU/Kommunedelplaner, Risiko- og Sårbarhedsanalyse. Technical report, Norwegian Public Roads Administration. (In Norwegian).

Danish Energy Agency (2012). *Eksempelsamling om Brandsikring af Byggeri 2012*. (In Danish).

Davis, G. A. (2003). Bayesian reconstruction of traffic accidents. *Law, Probability and Risk*, 2:69–89.

DBHA (2004a). *Information om Brandteknisk Dimensionering*. Danish Business and Housing Authority. (In Danish).

DBHA (2004b). *Tillæg 8 til Bygningsreglement 1995*. Danish Business and Housing Authority. (In Danish).

de Campos, L. M., Fernández-Luna, J. M., and Huete, J. F. (2004). Bayesian networks and information retrieval: An introduction to the special issue. *Information Processing and Management*, 40:727–733.

De Sanctis, G., Fischer, K., Kohler, J., Fontana, M., and Faber, M. H. (2011). A probabilistic framework for generic fire risk assessment and risk-based decision making in buildings. In Faber, M. H., Köhler, J., and Nishijima, K., editors, *Applications of Statistics and Probability in Civil Engineering*, pages 2000–2007. CRC Press.

DECA (2010). *Building Regulations 2010*. Danish Enterprise and Construction Authority.

DEMA (2013). *Redningsberedskabets Statistik 2013*. Dansih Emergency Management Agency, 2nd edition. (In Danish).

Der Kiureghian, A. and Ditlevsen, O. (2009). Aleatory or epistemic? Does it matter? *Structural Safety*, 31:105–112.

Donegan, H. A. (2002). Decision analysis. In DiNenno, P. J., editor, *SFPE Handbook of Fire Protection Engineering*, pages 5–8 – 5–23. National Fire Protection Association, 3rd edition.

Eckstein, M. and Maniscalco, P. M. (2006). Focus on smoke inhalation — The most common cause of acute cyanide poisoning. *Prehospital and Disaster Medicine*, 21:49–55.

Eisenhardt, K. M. (1989). Building theories from case study research. *The Academy of Management Review*, 14:532–550.

European Parliament (2004). *Directive 2004/54/EC of the European Parliament and the Counsil of 29 April 2004 on Minimum Safety Requirements for Tunnels in the Trans-European Road Network*. www.eur-lex.europa.eu.

Faber, M. H. (2012). *Statistics and Probability Theory*. Springer.

Frantzich, H. (1998). Risk analysis and fire safety engineering. *Fire Safety Journal*, 31:313–329.

Haggkvist, A. (2011). Fixed fire fighting systems in road tunnels. http://magazine.sfpe.org/fire-protection-design/fixed-fire-fighting-systems-road-tunnels. (Accessed June 28, 2014).

Hall, Jr., J. R. and Watts, Jr., J. M. (2008). Fire risk analysis. In Cote, A. E., editor, *Fire Protection Handbook*, pages 3–135 – 3–143. National Fire Protection Association, 20th edition.

Hanea, D. M. and Ale, B. (2009). Risk of human fatality in building fires: A decision tool using Bayesian networks. *Fire Safety Journal*, 44:704–710.

Hanea, D. M., Jagtmann, H. M., and Ale, B. (2012). Analysis of the Schiphol Cell Complex fire using a Bayesian belief net based model. *Reliability Engineering and System Safety*, 100:115–124.

Hansen, N. D. (2012). Development of a fire risk assessment model for tall residential buildings in Denmark. Master's thesis, Technical University of Denmark (DTU), Department of Civil Engineering, www.byg.dtu.dk/Undervisning/Afgangsprojekter.

Harmathy, T. Z. et al. (1989). A decision logic for trading between fire safety measures. *Fire and Materials*, 14:1–10.

Heckerman, D. (1990). Probabilistic similarity networks. *Networks*, 20:607–636.

Hede, M. B. (2011). Comparative evaluation of prescriptive, performance-based and risk-based fire safety in an office building. Master's thesis, Technical University of Denmark (DTU), Department of Civil Engineering, www.byg.dtu.dk/Undervisning/Afgangsprojekter.

Helton, J. C., Oberkampf, W. L., and Johnson, J. D. (2005). Competing failure risk analysis using evidence theory. *Risk Analysis*, 25:973–995.

Hofseth, M. (2012). Beredskapsanalyse E39 Rogfast. Technical Report 125, Norwegian Public Roads Administration. (In Norwegian).

Hokstad, P. R., Jenssen, G. D., Mostue, B. A., and Foss, T. (2012). E39 Rogfast — ROS Analyse, Tunnel. Technical Report A22149, SINTEF. (In Norwegian).

Holický, M. (2010). Fire risk assessment in buildings. In Soares, C. G., editor, *Safety and Reliability of Industrial Products, Systems and Structures*, pages 133–138. CRC Press.

Hovd, A. (1981). Trafikkulykker i vegtunneler. Technical Report A81012, SINTEF. (In Norwegian).

Høj, N. P. (2013). Risikovurdering af tung trafik i E39 Rogfast. Technical Report H-NO-171, HOJ Consulting. (In Danish).

ISO 31000 (2009). *Risk Management — Principles and Guidelines*. International Organization for Standardization.

Jensen, F. V. and Nielsen, T. D. (2007). *Bayesian Networks and Decision Graphs*. Springer, 2nd edition.

Karlson, B. and Larson, D. (2000). Using a Delphi panel for developing a fire risk index method for multistorey apartment buildings. Technical Report 3114, Lund University, Department of Fire Safety Engineering.

Körte, J. (2003). Risk-based emergency decision support. *Reliability Engineering and System Safety*, 82:235–246.

Lin, Y.-S. (2005). Estimations of the probability of fire occurrences in buildings. *Fire Safety Journal*, 40:728–735.

Magnusson, S. E., Frantzich, H., and Harada, K. (1996). Fire safety design based on calculations: Uncertainty analysis and safety verification. *Fire Safety Journal*, 27:305–334.

Matellini, D. B., Wall, A. D., Jenkinson, I. D., Wang, J., and Pritchard, R. (2013). Modelling dwelling fire development and occupant escape using Bayesian network. *Reliability Engineering and System Safety*, 114:75–91.

Meacham, B. J. (2002). Building fire risk analysis. In DiNenno, P. J., editor, *SFPE Handbook of Fire Protection Engineering*, pages 5–153 – 5–175. National Fire Protection Association, 3rd edition.

Meacham, B. J. (2010). Risk-informed performance-based approach to building regulation. *Journal of Risk Research*, 13:877–893.

Meacham, B. J., Bowen, R., Traw, J., and Moore, A. (2005). Performance-based building regulation: Current situation and future needs. *Building Research and Information*, 33:91–106.

Melby, K., Øvstedal, E., Amundsen, F. H., and Ranes, G. (2002). Subsea road tunnels in Norway. Technical Report 98, Norwegian Public Roads Adminitration.

Melchers, R. E. (2013). Human intervention and the safety of complex structural systems. *Civil Engineering and Environmental Systems*, 30:211–220.

Nathwani, J. S., Lind, N. C., and Pandey, M. D. (1997). *Affordable Safety by Chioce: The Life Quality Method*. University of Waterloo, Institute of Risk Research.

Neapolitan, R. E. and Jiang, X. (2007). *Probabilistic Methods for Financial and Marketing Informatics*. Morgan Kaufmann Publishers.

Nelson, H. E. and Mowrer, F. W. (2002). Emergency movement. In DiNenno, P. J., editor, *SFPE Handbook of Fire Protection Engineering*, pages 3–367 – 3–380. National Fire Protection Association, 3rd edition.

NFPA 550 (2012). *Guide to the Fire Safety Concept Tree*. National Fire Protection Association.

Nilsen, T. and Aven, T. (2003). Models and model uncertainty in the context of risk analysis. *Reliability Engineering and System Safety*, 79:309–317.

Nordby, B.-M. and Mjaaland, O. (2013). Havarikommisjonen inne i ulykkestunnelen. `www.vg.no/nyheter/innenriks/branner/havarikommisjonen-inne-i-ulykkestunnelen/a/10112629`. (In Norwegian). (Accessed April 2, 2014).

NPRA (2002). *Konsekvensutredning for E39 Kyststamvegen — Boknfjordkryssningen*. Norwegian Public Roads Administration. (In Norwegian).

NPRA (2007). *Guideline for Risk Analysis of Road Tunnels*. Norwegian Public Roads Adminitration. (In Norwegian).

NPRA (2010). *Manual 021 — Road Tunnels*. Norwegian Public Roads Adminitration. (In Norwegian).

NPRA (2014). E39 Rogfast. `www.vegvesen.no/Europaveg/e39rogfast`. Norwegian Public Roads Adminitration. (In Norwegian). (Accessed July 22, 2014).

Nystedt, F., Rantatalo, T., and Micheelsen, C. (2002). Quantifying the safety level in danish building fire regulations. In *4th International Conference on Performance-Based Codes and Fire Safety Design Methods*, pages 107–117. Society of Fire Protection Engineers.

Nævestad, T.-O. and Meyer, S. (2014). A survey of vehicle fires in Norwegian road tunnels 2008-2011. *Tunnelling and Underground Space Technology*, 41:104–112.

OECD (2001). *Safety in Tunnels — Transport of Dangerous Goods through Road Tunnels*. Organisation for Economic Cooperation and Development.

Parry, G. W. (1996). The characterization of uncertainty in probabilistic risk assessments of complex systems. *Reliability Engineering and System Safety*, 54:127–132.

Pearl, J. (1985). Bayesian networks: A model of self-activated memory for evidential reasoning. In *7th Conference of the Cognitive Science Society*, pages 329–334.

Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann Publishers.

Rahikainen, J. and Keski-Rahkonen, O. (2004). Statistical determination of ignition frequency of structural fires in different premises in Finland. *Fire Technology*, 40:335–353.

Rausand, M. (2011). *Risk Assessment*. Wiley.

Schubert, M., Høj, N. P., and Faber, M. H. (2012a). Etatsprogrammet moderne vegtunneler 2008-2011 — utvikling av risikoanalysemodell TRANSIT for vegtunneler. Technical Report 156, Norwegian Public Roads Adminitration.

Schubert, M., Høj, N. P., Ragnøy, A., and Buvik, H. (2012b). Risk assessment of road tunnels using Bayesian networks. *Procidia — Social and Behavioral Sciences*, 48:2697–2706.

Schön, D. A. (1983). *The Reflective Practitioner*. Basic Books Inc.

Shields, T. J., Silcock, G. W. H., Donegan, H. A., and Bell, Y. A. (1987). Methodological problems associated with the use of the Delphi technique. *Fire Technology*, 23:175–185.

Spearpoint, M., editor (2008). *Fire Engineering Design Guide*. New Zealand Centre for Advanced Engineering (CAENZ), 3rd edition.

The 4-City Coorperation (2013). *Vejledning om Brandsikring af Højhusbyggeri*. Municipalities of Aalborg, Odense, Aarhus and Copenhagen. (In Danish).

Vatn, J. (2011). Can we understand complex systems in terms of risk analysis? *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226:346–358.

Watts, Jr., J. M. and Hall, Jr., J. R. (2002). Introduction to fire risk analysis. In DiNenno, P. J., editor, *SFPE Handbook of Fire Protection Engineering*, pages 5–1 – 5–7. National Fire Protection Association, 3rd edition.

Williamson, J. (2013). Why Frequentists and Bayesians need each other. *Erkenntnis*, 78:293–318.

Winkler, R. L. (1996). Uncertainty in probabilistic risk assessment. *Reliability Engineering and System Safety*, 54:127–132.

Wolski, A., Dembsey, N. A., and Meacham, B. J. (2000). Accommodating perceptions of risk in performance-based building fire safety code development. *Fire Safety Journal*, 34:297–309.

Yeung, J. S. and Wong, Y. D. (2013). Road traffic accidents in Singapore Expressway tunnels. *Tunnelling and Underground Space Technology*, 38:534–541.

Yilmaz, D. (2013). Assessment of the fire risk levels in an office building and a nightclub with prescriptive designs. Master's thesis, Technical University of Denmark (DTU), Department of Civil Engineering.

Yin, R. K. (1981). The case study crisis: Some answers. *Administrative Science Quarterly*, 26:58–65.

Yung, D. (2008). *Principles of Fire Risk Assessments in Buildings*. Wiley.

Appendix A

Theory on Bayesian Networks

This appendix gives a basic introduction to Bayesian networks with regard to the mathematical background and the history of applications. The reader is assumed to have basic knowledge of (Bayesian) probability calculus.

A.1 History and Applications

In short, Bayesian networks are graphical models linking different causes and variables with outcomes through causal relations. Bayesian networks are based on Bayesian probability theory, i.e. probability is defined as subjective or a belief, and, therefore, they are also known as "Bayesian belief networks", "Bayesian probabilistic networks" or simply "belief networks".

Bayesian networks build on methods developed in the 1920s, however, the usage in its current form was developed in the 1980s by professor Judea Pearl of University of California at Los Angeles (Pearl, 1985, 1988). Originally, the methods developed by Pearl were applied in computer science to model artificial intelligence using informed decision-making based on Bayesian networks. Later, Bayesian networks has been used in robotic technology to model for example logical reasoning (Jensen and Nielsen, 2007).

In time, Bayesian network models have also been applied to very different fields such as medicine, where they are used to improve diagnoses (Heckerman, 1990), financial informatics (Neapolitan and Jiang, 2007), information retrieval (de Campos et al., 2004) and risk assessment, as TRANSIT is an example of (Schubert et al., 2012a). Even law (Davis, 2003) has seen applications of Bayesian networks due to their logic and consistency.

In risk assessments, Bayesian networks can be used to model systems more detailed and effective than e.g. fault and event trees as a binary representation is not needed. Additionally, the inherent use of conditional probabilities allow Bayesian networks to take interactions between systems into account in a way that for example fault trees cannot (Rausand, 2011).

Table A.1: Advantages and limitations of using Bayesian networks in risk assessment (Rausand, 2011).

Advantages	**Limitations**
+ The graph gives a good overview over the model with intuitive interpretations.	– Requires a workload that rapidly increase with the number of variables.
+ Can incorporate both qualitative and quantitative information.	– Requires use of computer program to calculate even simple networks.
+ Based on mathematically well-founded theory.	
+ Can be updated when new information becomes available.	
+ Can replace a fault tree analysis as part of a risk analysis, thereby adding flexibility as a binary representation is not required.	

Some of the general advantages and limitations of using Bayesian networks in risk assessment are listed in table A.1. The table shows that the limitations primarily relate to the workload and computational demands. On the other hand, the advantages allow modelling of complex systems with numerous variables without ending up with large confusing models. Additionally, Bayesian networks can be flexible in their way of handling information and the mathematical structure of the network allows modelling of highly interconnected phenomena. However, the data needed to construct conditional probability tables for complex systems may be scarce and, therefore, assumptions and expert judgement must often be used, although they introduce uncertainty to the model. Nonetheless, Bayesian networks are seen as a powerful mathematical and analytical tool (Rausand, 2011).

A.2 Definitions

A Bayesian network links different variables based on mutual relations. Each variable is described by a set of states — e.g. a variable A have n states denoted $(a_1, \cdots, a_n)$. The variables[1] are linked by directed edges[2], so the direction of the edge describes the mutual causal relationship between the variables — e.g. the variable "fire" may trigger the variable "fire alarm", whereas, activation of the fire alarm does not ignite a fire; thus, the direction will be from fire to alarm. However, the direction is not always obvious. Jensen and Nielsen (2007) describe different methods to figure out the direction in difficult cases.

[1]Also known as "nodes".
[2]Also known as directed "arcs".

Figure A.1 shows a simple example of a Bayesian network. A is called the parent of A and C, and B and C are called the children or descendants of A. Additionally, B is a parent to C. It is possible for a variable to have multiple parents and descendants, thus, allowing several variables to have an influence on a certain variable and vice versa. However, a variable can not be its own parent or descendant and, therefore, there can be no path $A_1 \to \cdots \to A_n$, so that $A_n = A_1$. Thus, there can be no "loops" or cycles in the network — therefore, a Bayesian network is called Directed Acyclic Graph (DAG) (Jensen and Nielsen, 2007).

As mentioned, traditionally, each variable has a finite number of states — e.g. for an electrical installation (on,off) or for the number of lanes on a road $(1,2,3,4)$ or for the number of persons in a room $([0,20],[21,40],[41,\infty[)$. Alternatively, a variable can be modelled as a continuous variable, which is described in section A.5. The probability of a variable to be in a certain state is dependent on the parents — this is called conditional probability. The conditional probabilities are organised in conditional probability tables for each variable. Such a table describes the probability of a variable to be in state a_i given any of the states of the parents. The conditional probability tables of the variables in the network seen in figure A.1 are $P(A|B)$ and $P(C|A,B)$. The unconditional probability table $P(A)$ is used for A as this variable has no parent.

To summarise, a Bayesian network is defined as a graph with the following four properties (Jensen and Nielsen, 2007):

- A set of *variables* and a set of *directed edges* between variables.
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed edges form a *Acyclic Directed Graph* (DAG).
- Each variable A with parents $\mathrm{pa}(A)$ has a conditional probability table attached — denoted $P(A|\mathrm{pa}(A))$. The unconditional probability table $P(A)$ is used, if A has no parents.

The following sections will elaborate further on some of the key terms in Bayesian network theory.

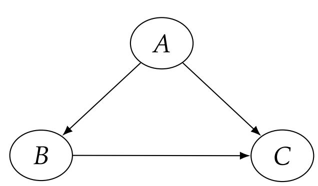


Figure A.1: A simple Bayesian network with three variables, A, B and C, and three directed edges $A \to B$, $A \to C$ and $B \to C$.

A.3 States and Evidence

As mentioned, the probability of a variable to be in a certain state depends on the states of the parent variables through the conditional probability tables. The so called chain rule for Bayesian networks is used to calculate the influence of one variable on another, thus, calculating the the joint probability distribution of a given network. The chain rule is given as seen in equation (A.1) (Jensen and Nielsen, 2007).

$$P(\mathcal{U}) = \prod_{i=1}^{n} P(A_i|\mathrm{pa}(A_i)) \tag{A.1}$$

Here, $\mathcal{U}$ is the set of all variables in the network and $P(\mathcal{U})$ is the unique joint probability distribution of the network. n is the number of variables, and $\mathrm{pa}(A_i)$ means the parents of A_i. Thus, $P(\mathcal{U})$ for the network seen in figure A.1 is:

$$P(\mathcal{U}) = P(C|A,B)P(B|A)P(A)$$

The probability distribution of a variable is updated when anything specific is known about the variable — for example if it is known that the number of lanes on the road is "2". The knowledge is called *evidence* and the update can be made through a *finding*. A finding on a variable is a vector containing only ones and zeros and is multiplied with the probability distribution vector of the variable. Thus, a variable can still have more than one state after the evidence is introduced, if the evidence merely excludes certain states. The sum of all probabilities of the different states is always 1, and after inserting evidence, the probability distribution is normalised in order to maintain this.

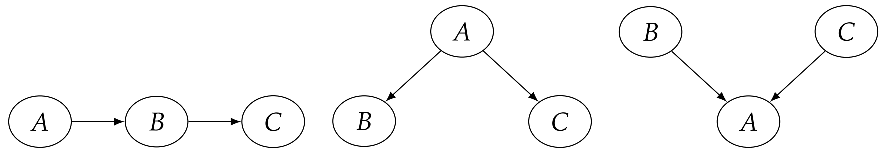
However, not all types of evidence can be described in this way. E.g. an expert say that the probability of a variable, A, to be in state a_1 may be twice as large as the probability of A to be in state a_2. This type of evidence is called "likelihood evidence" and can also be incorporated in Bayesian networks (Jensen and Nielsen, 2007).

Evidence that excludes all but one state of a variable is called "hard evidence". A variable is said to be instantiated, when it has received hard evidence (Jensen and Nielsen, 2007). As seen elsewhere in this work, basic variables such as geometry and existence of certain installations are instantiated, when using Bayesian networks in risk analysis of specific designs.

A.4 Connections and Separation

Basically, Bayesian networks have three different types of connections between variables as seen in figure A.2. The three types are serial, diverging and converging connections (Jensen and Nielsen, 2007).

Serial connections link a variable, A, with a variable C through a third variable B as seen in figure A.2(a). Evidence inserted in C will influence the probability of A through B and vice versa, thus, allowing information to flow between the variables. However, if B is instantiated the link is blocked and the probabilities of A and C are now independent.



(a) Serial connection. (b) Diverging connection. (c) Converging connection.

Figure A.2: The three different types of connections in Bayesian networks.

Diverging connections link a variable, A, to several children, B and C (and potentially more), as seen in figure A.2(b). Evidence inserted into B will influence the belief on the states of A, which in return will influence the belief on the state of C. However, instantiating A and the belief on B no longer influence the belief on C. Thus, information can flow between the children through the parent as long as the parent is not instantiated.

Converging connections link a variable, A, to several parents, B and C (and potentially more), as seen in figure A.2(c). Knowing something about B does not alter the belief on the states of C — cf. the chain rule in equation (A.1). However, evidence inserted into A (or a descendant of A) will update the belief on the states of the parents. Thus, information can only flow through a converging connection, if the child or any of its descendants have received evidence.

Based on the observations above, a connection that no longer allows information to pass through it will separate the variables making them independent of each other. Independent variables are said to be "d-separated"[3] and, to summarise, d-separation happens if either (i) the intermediate variable in a serial or diverging connection is instantiated or (ii) neither the child nor any of the descendants of the child in a converging connection have received evidence (Jensen and Nielsen, 2007). Variables that are not d-separated are said to be "d-connected".

A special set of variables for a variable, A, is the *Markov blanket*. The Markov blanket is as all the variables that are either a parent of A, a child of A or a variable sharing a child with A. The property of the Markov blanket is that A is d-separated from the rest of the network, when all the variables in the blanket are instantiated (Jensen and Nielsen, 2007).

A.5 Continuous Variables

Continuous variables are possible to model with Bayesian networks, which is a strength as many variables in nature are continuous — e.g. temperature, mass and pressure. However, Jensen and Nielsen (2007) states inclusion of continuous variables entail two constraints to the model. First, the continuous variable must be assigned a conditional Gaussian distribution. Each configuration of the discrete parents yields a constant value of the variance, whereas the mean is a linear function based on the continuous parents. Second, a continuous variable cannot have discrete descendants.

[3]"d" is an abbreviation for "directed graph".

These two constraints can make it complicated to implement continuous variables and, therefore, continuous variables are often modelled as discrete variables grouping values based on the application — e.g. temperature could be modelled with (low, high, very high) as states or by using simple intervals such as $([0,30[, [30,80[, [80,\infty[)$ (Jensen and Nielsen, 2007).

Appendix B

Road Tunnel Safety

This appendix gives an introduction to road tunnel safety. The contents are key to understand the reasoning behind the Bayesian network model TRANSIT.

The primary challenges in road tunnel safety are preventing traffic accidents, tunnel fires and accidents involving hazardous materials. The Norwegian road tunnel guideline (NPRA, 2010) has been used to exemplify how the challenges can be coped with.

B.1 Traffic Accidents in Road Tunnels

Generally, road tunnels are as safe or safer than similar roads in open air if the accident rate is considered (i.e. the number of accidents per kilometre per year). However, the severity of the common road tunnel accidents are often greater (Nævestad and Meyer, 2014). Therefore, special consideration with respect to the safety and comfort of the users is needed due to the enclosed environment.

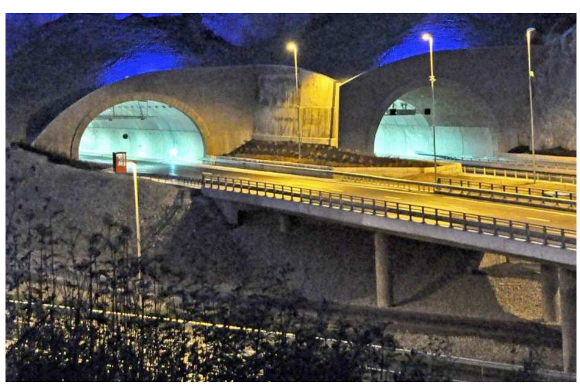


Figure B.1: The section around the tunnel portals has a higher risk compared to in the middle sections (NPRA, 2010).

Figure B.2: Artistic light patterns are projected onto the tunnel wall in order to break monotony of the tunnel (Melby et al., 2002).

Typically, accident data from road tunnels show that the accident rate is higher in some parts of the tunnel compared to others (Hovd, 1981). Recent research show the same trend and both Nævestad and Meyer (2014) and Yeung and Wong (2013) found that the accident rate can be much higher in the entrance zone than deeper in the tunnel[1], however, the severity of accidents are higher in the middle part of tunnels. The Norwegian road tunnel guideline (NPRA, 2010) describes different design aspects that should be considered in order to minimise accidents near the tunnel entrance. The idea is to make the driving experience as continuous as possible when entering the tunnel.

Melby et al. (2002) states that most accidents in Norwegian road tunnels have been accidents between vehicles driving in the same direction (catch-up collisions or accidents due to overtaking) and single vehicle accidents. Such accidents can be mitigated by constructing crawler lanes in steep tunnels, i.e. tunnels with a gradient larger than 5 % (NPRA, 2010). Melby et al. (2002) also found that the accident rate in short tunnels were higher than in longer tunnels even though a correction for the higher accident rate in the entrance zone was made.

Human factors that influence accidents in road tunnels include difference between the level of illumination between the road in open air and the tunnel, lack of references to surroundings, monotony and fear (Nævestad and Meyer, 2014). Figure B.2 shows how lighting can be used to decrease monotony, thus, decreasing the risk of accidents. Also, Norwegian tunnels regulated by NPRA (2010) have demands with respect to the lighting in the tunnel in order to avoid drivers to be blinded by differences in the level of illumination. Another way to reduce accidents rates is having tunnels with two tubes and unidirectional traffic in order to avoid drivers to be distracted by oncoming traffic.

[1] 3-4 times as high according to Nævestad and Meyer (2014).

B.2 Fire in Road Tunnels

One of the main safety concerns in most tunnels is the risk of fire as heat and smoke often only can be removed through the tunnel tubes, which compromises both evacuation as well as fire fighting and rescue operations. Tunnel fires most often starts in a vehicle as the tunnel surface and installations are made mainly of non-combustible materials. Ignition of vehicles can be caused by several events including accidents, technical failures and overheating of brakes or engine due to the gradients in the tunnel — typically, the gradients are largest in sub-sea tunnels, but gradients are seen in most tunnels. Norwegian sub-sea tunnels are typically very deep due to the deep fjords, and gradients up to 10% are seen in some tunnels (Melby et al., 2002).

Nævestad and Meyer (2014) found that the ignition source for light and heavy vehicles differ — light vehicles are most often ignited following a traffic accident, whereas fires in heavy goods vehicles (HGVs) typically are started by technical failures. The study also found that sub-sea tunnels were overrepresented in the fire statistics. According to Nævestad and Meyer (2014), the reason is that sub-sea tunnels typically are longer, have higher gradients and have long distances with high gradients.

Additionally, initiation of a tunnel fire is suggested to be influenced by traffic volume, the share of HGVs, the age of the vehicles and the competence and experience of the driver (Nævestad and Meyer, 2014).

B.2.1 Historic Road Tunnel Fires

Although most tunnel fires incidents do not cause harm to persons, the potential to do much harm is present (Nævestad and Meyer, 2014). This has been seen in numerous cases including the Mont Blanc tunnel fire in 1999, where 39 people died, when a HGV caught fire (ATMB, 2014), the Gotthard tunnel fire in 2001, where two HGVs collided causing a fire that killed 11 people (Carvel and Marlair, 2005). Another notable incident is the Caldecott tunnel fire being one of the few severe tunnel fires mainly fuelled by a hazardous material, in this case 33000 litres of gasoline (OECD, 2001).

In Norway, extraordinary tunnel fires have occurred in the Oslofjordtunnel in June 2011 (AIBN, 2013) and, recently, in the Gudvangatunnel in August 2013 (Nordby and Mjaaland, 2013) — both incidents involved a HGV that caught fire due to a mechanical defect. Based on the incidents, the Accident Investigation Board Norway expressed concern that the risk of fires in HGVs might be underestimated in Norwegian bi-directional road tunnels and stated that the Norwegian Public Roads Administration did not have updated risk pictures of the tunnels (AIBN, 2013).

B.3 Accidents involving Hazardous Materials

Another important safety issue in road tunnels is accidents involving hazardous materials. A study by OECD (2001) identified the most severe consequences from

Table B.1: Grouping of hazardous materials based on possible consequences of accidents in road tunnels (OECD, 2001).

Group	Description
A	All goods allowed on open roads.
B	As group A except goods that may lead to a "hot" BLEVE.
C	As group B except goods that may lead to a "cold" BLEVE or a large release of toxic gas.
D	As group C except goods that may lead to a large fire.
E	No hazardous goods (except those who require no special marking on the vehicle).

road tunnel accidents involving hazardous materials. In order of severity, they are a "hot" BLEVE[2,3], a "cold" BLEVE[4], a large release of toxic gas and a large fire.

OECD (2001) proposes to group hazardous materials into five groups based on the potential for the consequences mentioned above. The groups are presented in table B.1. The groups allow controlling the types of goods passing through the tunnel — e.g. only group D and E goods may pass through the tunnel during rush hour in order to minimise possible casualties in case of an accidents.

Both OECD (2001) and NPRA (2010) propose that risk assessment of transport of hazardous goods through road tunnels imply analysis of the risk of personnel injuries both when transporting the goods through the tunnel and when using an alternative route.

[2]BLEVE means Boiling Liquid Expanding Vapour Explosion (OECD, 2001).
[3]A "hot" BLEVE is a BLEVE of flammable gas that ignites upon explosion (OECD, 2001).
[4]A "cold" BLEVE is a BLEVE of non-flammable gas that does not ignite (OECD, 2001).

Appendix C

TRANSIT Networks

Figures C.1 and C.2 show the Bayesian networks used in TRANSIT — network A and B, respectively. The colours of the nodes indicate which type of node they are:

- Orange: Key performance indicator (KPI)
- Yellow: Non-observable indicator (NOI)
- Grey: Logical non-observable indicator (LNOI)
- Blue: Outcome

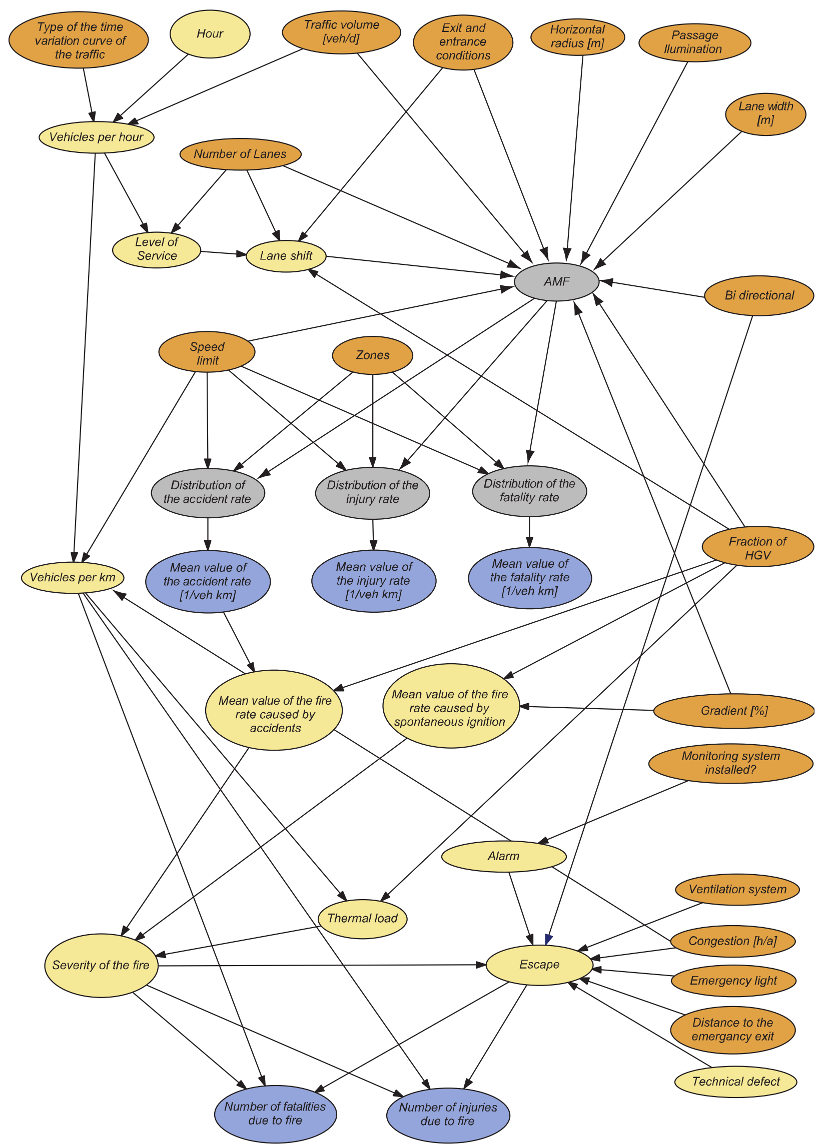


Figure C.1: The Bayesian network for accident and fire rates (network A) (Schubert et al., 2012a).

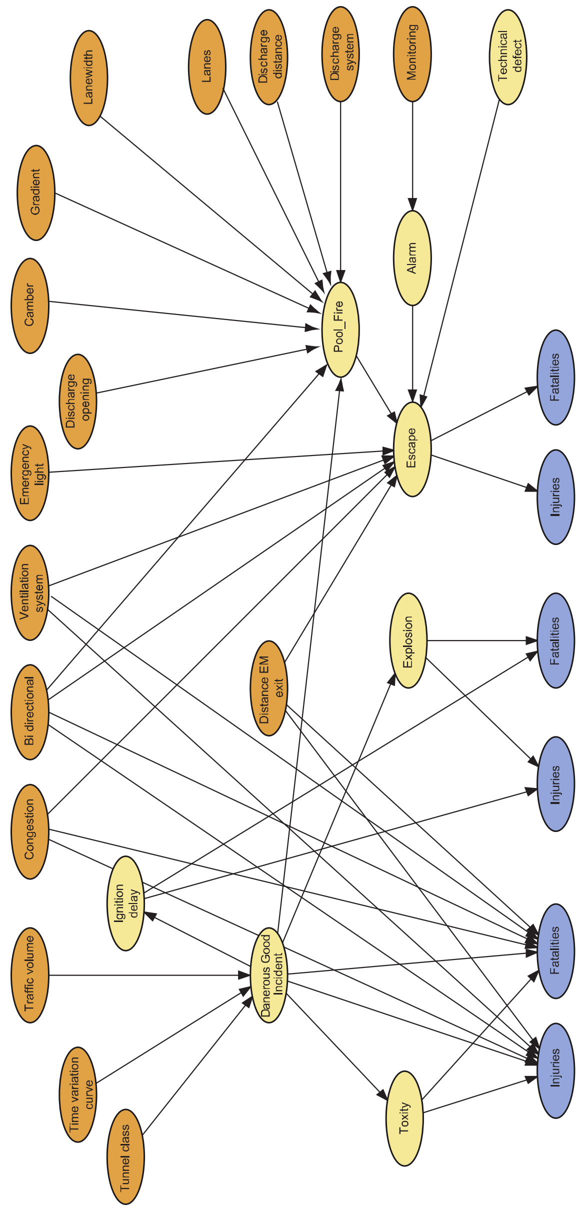


Figure C.2: The Bayesian network for accidents with hazardous materials (network B) (Schubert et al., 2012a).